HOW ACTIVITY MONITOR USE IS ASSOCIATED WITH MOTIVATION AND PHYSICAL ACTIVITY BEHAVIOR

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ABSTRACT

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Wearable physical activity (PA) monitors have been adopted by millions of people across the United States, but we do not fully understand who wears them and why. The devices have been promoted as a tool that motivates users by collecting data on their daily activities and delivering tailored feedback based on predetermined goals. The purpose of this dissertation was twofold: 1) To describe users of activity monitors detailing how and why they used this technology, and 2) To explore the motivational profile of activity monitor users and assess how it is related to PA. This dissertation consists of a series of two separate but related studies.

The first study recruited over 2000 activity monitor users from across the United States to complete a web-based survey describing why they used this technology and how they interacted with their device. This study showed significant differences in sociodemographic and use characteristics between current and former users and between women and men. Activity monitors were perceived by users as influential on

their PA behavior and differences in use patterns between subgroups warranted further exploration of associations between user characteristics, motivation to exercise, and PA.

The second study investigated the motivation and PA of activity monitor users. While activity monitors have been widely promoted as a means to motivate users to be more active, the motivational profile of users has never been assessed. While all motivational regulations were significantly correlated with PA, the strongest associations were with the more self-determined motives (integrated, identified and intrinsic respectively). Five motivational profiles emerged from the cluster analysis: ‘High Amotivation’ (n=30), ‘Autonomous with High Introjected’ (n=101), ‘Low Overall Motivation’ (n=61), ‘High Controlled Motivation (n=47), and ‘Autonomous with Low Introjected’ (n=81). Profiles characterized by more autonomous regulations had higher levels of PA.

These studies offer new insights on who activity monitor users are, why they decide to use this technology, and how they interact with their devices. While the second study identified an association between motivational profiles and PA, further longitudinal research is needed to assess whether use of an activity monitor impacts the direction and/or magnitude of this relationship.

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C.P.F.

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INTRODUCTION

Background

Physical inactivity is broadly recognized as a key contributing factor to mortality and morbidity (Lee et al., 2012). Despite this, widespread attempts to promote physical activity (PA) through government policies and community programs have had limited success, and prevalence of insufficient PA remains high (Chan & Woo, 2010). Some researchers have called for a renewed focus on behavior change at personal and interpersonal levels, using strategies such as self-monitoring and tailored feedback (Burke, Wang, & Sevick, 2011; Chan & Woo, 2010). While these strategies have been applied previously with mixed results, new technologies such as wearable activity monitors may allow for key elements to be delivered in a more efficient manner; an example being the ability for PA data to be collected and immediately analyzed, with personalized feedback offered to users.

While research supports behavior change interventions at personal and interpersonal levels, the role technology plays in delivering these interventions is not well understood, and its effectiveness in impacting behavior change is unclear. Wearable activity monitors have been widely adopted by consumers in recent years, with almost 100 million devices sold globally in 2016, and this number is projected to climb to over 200 million by 2021 (Ubrani, 2017). Based on this rapid growth, it is understandable why many see these devices as possessing great potential to influence PA. They seem to support many effective behavior change techniques: tracking activity, offering tailored feedback, and enabling sharing of data within social networks. Advertisements for activity monitors proclaim their ability to motivate users to become more active (Fitbit, 2017), and numerous researchers have stated that the potential of these devices lies in their motivational capability (Bassett, 2012; Hickey & Freedson, 2016). However, while some studies have shown improvements in PA after activity monitor use, effectiveness in changing PA habits has been limited in clinical trials, with many showing inconsistent outcomes (Goode et al., 2016). Reasons for these varied findings are unclear, but factors that have not been widely explored include the psychosocial correlates of PA among activity monitor users, and the influence of individual characteristics on behavioral outcomes. Who uses these devices volitionally, and how they are used outside of clinical trials, is not well-understood. Furthermore, it is not clear how these devices are associated with motivation, a recognized psychosocial correlate of PA according to (Bauman, Sallis, Dzewaltowski, & Owen, 2002), supporting a need for additional investigation.

Self Determination Theory (SDT), a commonly used theory when examining motivation, posits that the type, rather than a particular amount, of motivation is critical when trying to establish long-term behavior change. Motivation, according to SDT, exists on a continuum, comprising intrinsic and extrinsic components, representing varying degrees of autonomy. Research by Duncan, Hall, Wilson, and Jenny (2010) found more autonomous types of motivation (intrinsic, integrated, identified) were associated with greater levels of exercise frequency, intensity and duration, while Hagger and Chatzisarantis (2008) found autonomous regulation was also associated with greater exercise adherence.

While activity monitors have been promoted as tools to motivate users to become more active, research suggests that they may have a mixed or even a negative effect. Therefore, to more comprehensively understand how activity monitors are associated with users' behaviors, further research is necessary to investigate both their association with each individual motivation category as well as the overall motivational profile of each user.

Significance

Wearable activity monitors have been broadly adopted by the general population, and they are regularly used in physical activity research interventions. A major limitation of the current research is a lack of data on the reasons for using this technology, and the motivational characteristics and profile of activity monitor users. To address this gap in the literature, this dissertation consists of two studies; the first examining the personal and behavioral characteristics of users, and the second assessing the motivation of activity monitor users and identifying how motivational profiles relate to PA behavior. The specific aims of this dissertation were:

Q.1: To describe activity monitor users across the United States, detailing their sociodemographics, PA behavior, and their experiences of using the devices.

Q.2: To measure the magnitude of each dimension of the motivation continuum and identify associations between motivational regulations and PA among activity monitor users.

Q.3: To determine if combinations of motivational regulations exist among activity monitor users and to compare the PA behavior of these clusters.

Dissertation Organization

This dissertation examines the use of activity monitoring technology and reports on the associations between motivation and PA in users of this technology. The first study, discussed in Chapter II, describes the sociodemographic profile of users, their PA behavior, and how they interact with their devices. The second study, discussed in Chapter III, builds on the research presented in Chapter II by assessing the motivational profile of activity monitor users and explores how motivation is associated with PA. A comprehensive review of the literature in this area of research can be found in Appendix B. Supplemental data from Study I can be found in Appendix C and for Study II in Appendix D. The complete list of survey questions from Study I can be found in Appendix E and the survey for Study II can be found in Appendix F.

Chapter II

WHO WEARS PHYSICAL ACTIVITY MONITORS AND WHY? CHARACTERISTICS OF USERS IN THE UNITED STATES

Abstract

Background: There has been an explosion in the use of wearable physical activity monitors, but we do not fully understand who wears them and why.

Purpose: To describe sociodemographics, physical activity (PA) behavior, reasons for device use, and compare across subpopulations.

Methods: Current and former activity monitor (AM) users (*N*=2117) recruited across the United States completed a web-based survey. Sociodemographics, PA, health information, and AM use were queried. Descriptives are reported as means, standard deviations (SD), and frequencies. Independent t-tests and chi-square analysis were used to compare groups.

Results: Overall respondents were 18-81 years old (32.9 ± 12.1) with 73.4% women. A majority were current AM users (68.7%). The average number of months of AM use was 9.4 ± 9.8 and a majority of both current and former users reported the AM contributed to them increasing levels of PA. Significant differences were found in sociodemographic and use characteristics between current and former users and between women and men.

Conclusion: Activity monitors were perceived by respondents as influential on their PA behavior. Differences in use patterns between subgroups supports further exploration of associations between user characteristics, motivation to exercise, and PA.

Background

In the United States, physical inactivity is associated with a number of non-communicable diseases (Blackwell, Lucas, & Clarke, 2014; World Health Organization [WHO], 2014), including type 2 diabetes, cardiovascular disease, and some cancers (Lee et al., 2012). As the public manifestation of the deleterious effects of physical inactivity grows more evident, figuring out how best to promote positive changes in PA behavior is of paramount importance. Major steps have already been taken, such as the development of explicit guidelines for the general public on the volume and intensity of PA needed to reduce disease risk (Garber et al., 2011; Haskell et al., 2007; Physical Activity Guidelines Advisory Committee, 2008). However, only about 20% of the population self-report meeting those guidelines (Carlson, Fulton, Schoenborn, & Loustalot, 2010), and this is worse when measured using accelerometry. For example, accelerometer-measured data from the National Health and Nutrition Examination Survey (NHANES) found only 9.5% of men and 7% of women met the recommended levels of aerobic PA (Tucker, Welk, & Beyler, 2011).

The reasons for poor adoption of, or a lack of adherence to, the recommended levels of PA are varied and complex (Bauman et al., 2012; Rhodes, Warburton, & Murray, 2009), but a sizable body of research has identified a relationship between the use of monitoring devices and increased PA (Kang, Marshall, Barreira, & Lee, 2009;

Vaes et al., 2013). For example, numerous studies have shown pedometers to be effective in increasing PA (Bravata et al., 2007), and more recent research has suggested that wearable devices might be helpful in motivating users to be more active (Bassett, 2012; Hickey & Freedson, 2016). For example, in their study of overweight postmenopausal women, Cadmus-Bertram, Marcus, Patterson, Parker, and Morey (2015a) found use of the Fitbit One device led to significant increases in total MVPA, duration of MVPA and total steps taken among the intervention group, versus a control group who did not wear a device.

While the research on wearable activity monitors is promising, it is still a relatively new area of study. The majority of research to date has focused on assessing device validity (Welk, McClain, & Ainsworth, 2012), with several other studies focusing on other factors, such as whether the monitors are feasible in specific age groups or for those with a chronic disease (McMahon et al., 2016; Mercer, Giangregorio, et al., 2016; Naslund, Aschbrenner, Barre, & Bartels, 2015). Thus, a significant barrier to deciphering the potential of this technology for increasing physical activity levels is that the user characteristics and behavior of those who use activity monitors are still somewhat of an unknown entity. Limited data are available from sources such as the Pew Research Center on health tracking by Americans (Fox & Duggan, 2013), or from market research companies (Ledger & McCaffrey, 2014), but the peer-reviewed literature lacks research describing users, their rationale for use or underlying behavioral predictors of PA such as motivation to exercise.

More specifically, in most studies to date participants have been mandated to wear a device as part of the research protocol rather than being included because they were already activity monitor users. Due to the lack of evidence on those who choose to be voluntary users of this technology the potential impact on PA in free-living situations remains ambiguous. It is unclear how differences, such as user characteristics (e.g. age or gender), the context in which the device is used (e.g. while training alone for a marathon or as part of a group having a weight loss competition), or how it is used (all the time or infrequently), impact psychosocial predictors of exercise or PA behaviors. As such, the aim of this investigation was twofold: 1) to address a gap in the research by describing users' sociodemographics, PA behavior, and reasons for adopting activity monitors; and 2) to assess if any of these characteristics are associated with gender or user status (current or former).

Methods

Study Design

The purpose of this study was to gather information about activity monitor use in the United States. A variety of internet-based modes, such as social media, online forums and classifieds (e.g. Facebook, Twitter, LinkedIn, Craigslist), were employed to locate users across the United States. Postings were made on local Craigslist sites in each state to ensure a wide distribution. Based on reports of devices sold (Ubrani, 2017), activity monitor users make up a small percentage of the overall population. Therefore, we did not use a probability-based sampling approach to find users, as it would have been an impractical means of reaching our target audience and prohibitively expensive. The target audience was likely internet users, as most wearable devices require an email address to sign up for use. Similar non-probability sampling techniques have been being growing in popularity in recent years, with the NIH currently using this method to recruit for its ‘All of Us’ precision medicine initiative (Yank, Agarwal, Loftus, Asch, & Rehkopf, 2017). The survey comprised validated questionnaires along with specific questions on health technology.

Participants

Participants were recruited between November 2015 and January 2017. The research posting included a link to the Survey Monkey platform, which was used for data collection. Inclusion criteria were being 18 years or older, a resident of United States, and a current or former user of a wearable activity monitor. The research description also explained what was meant by ‘wearable activity monitors’ with examples given of common brands such as Fitbit and Jawbone.

The survey included 55 questions and, on average, took less than 10 minutes to complete. Before being allowed to proceed to the survey, respondents were required to complete an informed consent page acknowledging they met inclusion criteria and understood the procedures, risks and benefits of the study. All participants were asked to give details on the make and model of device they used, thus reducing the likelihood of non-activity monitor users attempting to respond. All those completing the survey entered a lottery to win a $100 gift card, with their chance of winning set at 1 in 500 or better. All procedures were approved by the Teachers College, Columbia University Institutional Review Board. The survey questions can be reviewed in Appendix E.

Measures

The survey was designed with the aim of finding information on the sociodemographic characteristics of each user, their health and PA behaviors, and how they used their activity monitors. As activity monitor use is a relatively new phenomenon, this survey combined validated questionnaires alongside questions inspired by healthcare technology surveys such as the PEW Internet Research Survey (Fox & Duggan, 2013). The survey was broken into four major sections, detailed below. A majority of questions offered a selection of pre-populated answers for respondents to select from, with the option given for open-ended responses where appropriate.

Sociodemographic profile. Participants reported age, gender, race/ethnicity, income, employment status, education level, relationship status, and ZIP code.

Health profile. Participants were asked to report height, weight, any diagnosed medical conditions and to give a subjective rating of their own health status. Body Mass Index (BMI) was calculated using height and weight. Participants were asked if they were current cigarette smokers, with those responding in the affirmative asked to provide additional data on how long they had been smoking for and approximately how many cigarettes they smoked each day.

Physical activity profile. The Godin Leisure Time Questionnaire, a 7-day PA recall questionnaire that reports on average how many bouts (15 minutes or greater) of mild, moderate and strenuous activity participants complete, was used to assess PA levels (Godin & Shephard, 1985). Respondents were asked their reasons for exercising, preferred mode(s) of exercise, and to rate whether they believed the quantity of PA they did each week was insufficient, appropriate or excessive. Perceived PA has been queried on national surveys such as NHANES and the National Health Interview Survey (NHIS). It has been found to be a predictor of future PA behavior and mortality (Zahrt & Crum, 2017).

Activity monitor use profile. Participants identified as current or former activity monitor users, noted the brand and model of device they used, and how long they had been wearing/had worn the device. From a series of drop-down menus, they identified where they got the device from (purchased themselves or as a gift), their reason(s) for device use, and, for those who no longer wore a monitor, their reason for stopping use. They also reported how often they checked their device each day, activity monitor adoption among their social circle (i.e. friends, family), and with whom, if anyone, they shared their data. They reported how wearing the device had influenced their PA behavior and, for those current users, whether or not they intended to continue using it for at least another 3 months.

Data Analysis

All analyses were conducted using SPSS Statistics 24.0 software (Macintosh version 24.0 SPSS Inc). Descriptive data are reported as means, medians, interquartile ranges and standard deviations (SD) for continuous variables, while frequencies and percentages are given for categorical variables. Two user groups were compared using independent t-tests (continuous data) and chi-square tests (categorical data). Groups were categorized by gender (female vs male) and device use status (current vs former user). The Benjamini-Hochberg False Discovery Rate (FDR) procedure was used to correct for alpha-inflation due to multiple comparisons. This procedure controls for the FDR, i.e. the expected fraction of null hypotheses rejected mistakenly (Benjamini &

Hochberg, 1995). Unlike many other methods, the FDR operates on actual significance levels achieved, providing a practical compromise to more conservative methods, such as the Bonferroni (Sedgwick, 2014).

Results

Of the 2826 respondents who gave informed consent, 2377 (84.1%) completed all questions. A majority of respondents (83%) were recruited via postings on Craigslist sites. Based on reported ZIP codes, all 50 US states (and Washington, DC) were represented. Of the completed surveys, 260 were excluded based on the following criteria: (1) having implausible values in their reported height, weight, or duration of device use; (2) having multiple surveys submitted from the same email address; or (3) reporting the use of an app (phone application) without an associated wearable activity monitor, heart rate monitor (without accelerometer) or basic pedometer instead of an activity monitor. Of the remaining 2117 respondents, 1454 (68.7%) were categorized as current activity monitor users, and 663 (31.3%) were categorized as former users.

Sociodemographic Profile

The overall sample was 73.4% women and ranged in age from 18 to 81. The average age of current users was 33.6 (± 12.2) and of former users was 31.5 (± 11.9). Table 1 displays the characteristics of the survey respondents overall and by current or former user. Respondents were highly educated with 63.2% having at least a bachelor's degree. Almost half identified themselves as living in an urban area (1043, 49.3%), with 888 (41.9%) classifying their home as suburban, and 186 (8.8%) rural.

Table 1

Sociodemographic Characteristics of Activity Monitor Users

	Overall (n=2117)	Current Users (n=1454)	Former Users (n=663)	p-value^
Gender (Female), n (%)	1553 (73.4%)	1075 (73.9%)	478 (72.1%)	0.38
White/Caucasian, n (%)	1349 (63.7%)	945 (65.0%)	404 (60.9%)	0.07
Bachelor's degree or higher, n (%)	1339 (63.2%)	939 (64.6%)	400 (60.3%)	0.06
Household Income, n (%)				<0.001**
< $50,000	949 (44.8%)	614 (42.2%)	335 (50.5%)	
$50,000-$99,999	653 (30.8%)	477 (32.8%)	176 (26.5%)	
≥ $100,000	344 (16.2%)	257 (17.7%)	87 (13.1%)	
Prefer not to answer	171 (8.1%)	106 (7.3%)	65 (9.8%)	
In a cohabiting relationship, n (%)	966 (45.6%)	709 (48.8%)	257 (38.8%)	<0.001**
Employment status, n (%)⌘				
Employed: full-time	1019 (48.1%)	751 (51.7%)	268 (40.4%)	<0.001**
Employed: part-time	373 (17.6%)	247 (17.0%)	126 (19.0%)	0.26
Student: full-time	465 (22.0%)	293 (20.2%)	172 (25.9%)	0.003**
Student: part-time	99 (4.7%)	64 (4.4%)	35 (5.3%)	0.38
Not employed, looking for work	194 (9.2%)	117 (8.0%)	77 (11.6%)	0.008**
Retired	72 (3.4%)	57 (3.9%)	15 (2.3%)	0.05
Other	167 (7.8%)	99 (6.8%)	68 (10.2%)	0.23

^ = chi-square analysis. ⌘ = respondents allowed to choose more than one category, therefore each row represents positive responses only. * = significant difference between groups; ** = remains significant after Benjamini-Hochberg correction for multiple comparisons.

Health and Physical Activity Profile

Table 2 displays the health and PA characteristics of respondents. Overall, more than half (53.2%) rated their health as very good or excellent, with less than 2% reporting their health as poor. Mean BMI overall was 26.8 (± 6.6), with BMI of current users (27.2 ± 6.7) higher than that of former users (26.0 ± 6.4). Almost a third (30.9%) of users overall had at least one diagnosed medical condition, with an additional 17.7% reporting multiple conditions. A full list of medical conditions can be seen in Appendix C, with the most common reported by this population being mental health disorders (14.6%), asthma (14.5%) and hypertension (9%).

A small proportion of respondents (16.7%) reported that they were not currently doing any form of exercise. Of those who reported being current exercisers, the median Godin Leisure Score Index was 45. A threshold of 24 on the MVPA sections of the Godin Questionnaire was used to determine if respondents could be classified as meeting weekly PA recommendations (Amireault & Godin, 2015), with 78.1% of those currently exercising considered sufficiently active. However, a majority (59.5%) believed that they did too little exercise when asked whether they felt they were active enough.

Primary reasons for exercising (detailed in Table 3) were weight loss (75.1%) and stress relief (74.7%), with aesthetic benefits (62.1%) and disease risk reduction (45.9%) also identified as important reasons. Exercise preferences differed by gender and between current and former users.

Table 2

Health and Fitness Characteristics of Activity Monitor Users

	Overall (n=2117)	Current Users (n=1454)	Former Users (n=663)	p-value^
Health rating, n (%)				0.15
Excellent	285 (13.5%)	193 (13.3%)	92 (13.9%)	
Very Good	841 (39.7%)	597 (41.1%)	244 (36.8%)	
Good	757 (35.8%)	508 (34.9%)	249 (37.6%)	
Fair	197 (9.3%)	136 (9.4%)	61 (9.2%)	
Poor	37 (1.7%)	20 (1.4%)	17 (2.6%)	
Medical Condition(s), n (%)				0.031*
None	1089 (51.4%)	721 (49.6%)	368 (55.5%)	
One	654 (30.9%)	461 (31.7%)	193 (29.1%)	
More than one	374 (17.7%)	272 (18.7%)	102 (15.4%)	
Current smoker, n (%)	168 (7.9%)	101 (6.9%)	67 (10.1%)	0.013**
Current Exerciser, n (%)	1784 (84.3%)	1272 (87.5%)	512 (77.2%)	<0.001**
Perceived Exercise Volume, n (%)				0.61
Much too much	10 (0.6%)	5 (0.4%)	5 (1.0%)	
Somewhat too much	33 (1.8%)	23 (1.8%)	10 (2.0%)	
Slightly too much	65 (3.6%)	43 (3.4%)	22 (4.3%)	
About the right amount	611 (34.2%)	446 (35.1%)	165 (32.2%)	
Slightly too little	610 (34.1%)	436 (34.3%)	174 (34.0%)	
Somewhat too little	312 (17.4%)	221 (17.4%)	91 (17.8%)	
Much too little	143 (8.0%)	98 (7.7%)	45 (8.8%)	

^ = chi-square analysis. * = significant difference between groups; ** = remains significant after Benjamini-Hochberg correction for multiple comparisons.

Table 3

Exercise Preferences of Activity Monitor Users

	Overall (n=2117)	Current Users (n=1454)	Former Users (n=663)	p-value^
Reason for Exercising⌘, n (%)				
Social Aspect	348 (19.5%)	232 (18.2%)	116 (22.7%)	0.38
Weight Management	1339 (75.1%)	980 (77.0%)	359 (71.1%)	<0.001**
Stress Relief	1333 (74.7%)	949 (74.6%)	384 (75.0%)	0.001**
Aesthetics	1107 (62.1%)	776 (61.0%)	331 (64.6%)	0.14
Training for an event/sport	312 (17.5%)	214 (16.8%)	98 (19.1%)	0.97
Disease risk reduction	819 (45.9%)	602 (47.3%)	217 (42.4%)	<0.001**
Other	152 (8.5%)	109 (8.6%)	42 (8.4%)	0.40
Preferred Mode of Exercise⌘, n (%)				
Lifting Weights	794 (37.5%)	545 (37.5%)	249 (37.6%)	0.97
Walking	1338 (63.2%)	990 (68.1%)	348 (52.5%)	<0.001**
Running	954 (45.1%)	681 (46.8%)	273 (41.2%)	0.015**
Hiking	446 (21.1%)	327 (22.5%)	119 (17.9%)	0.017**
Biking	462 (21.8%)	333 (22.9%)	129 (19.5%)	0.08
Swimming	270 (12.8%)	185 (12.7%)	85 (12.8%)	0.95
Dancing	314 (14.8%)	216 (14.9%)	98 (14.8%)	0.96
Aerobics	274 (12.9%)	206 (14.2%)	68 (10.3%)	0.013*
Yoga	521 (24.6%)	359 (24.7%)	162 (24.4%)	0.90
Pilates	147 (6.9%)	105 (7.2%)	42 (6.3%)	0.46
Playing Team Sports	192 (9.1%)	129 (8.9%)	63 (9.5%)	0.64

^ = chi-square analysis. ⌘ = respondents allowed to choose more than one category, therefore each row represents positive responses only. * = significant difference between groups; ** = remains significant after Benjamini-Hochberg correction for multiple comparisons.

Activity Monitor Use Profile

Median wear time for current users was 7 months (range 1-78 months), and 6 months among former users (range 1-78 months). A majority of both current (76.3%) and former (53.4%) users reported that the device had a positive influence on the amount of PA they did.

Over 100 different models of activity monitor were reported, with the Fitbit brand the most popular; 68.9% of current and 58.4% of former users having adopted this brand. Other popular brands were Apple, Jawbone, Garmin, Samsung and Nike. Current users reported a high level of interaction with their activity monitors, with over 90% checking their devices daily, and a third of users checking the device at least hourly. Close to half of respondents (48.3%) reported the use of smartphone applications to support their goals. Popular applications included Apple Health, Samsung Health, MapMyRun, Lose It!, Runtastic, MyFitnessPal, Nike Running and Weight Watchers.

Tables 4 and 5 offer data on why people used these devices and how they used the data. When asked who else they knew with a wearable device, most users reported having at least one or more (84.3%) person in their social circle who also wore an activity monitor, with friends (60%) and work colleagues (36%) the most common connection. Despite this ubiquity of activity monitors among their peer group, a surprisingly large proportion did not share any of their data with others, with 37.8% of current users and 47.7% of former users opting to keep their information to themselves.

The top reasons given by current users for using an activity monitor were an interest in monitoring their health variables (69.6%), an interest in trying out the technology (54.5%) and as an aid to weight loss (51.9%). A large majority of former users (71.5%) reported their interest in trying out the new technology as a key factor, with monitoring of health variables (44.6%) and as an aid to losing weight (36.2%) less important among this group. Those who purchased the device themselves reported a positive effect on their PA more often than those who received it as a gift (p<0.001).

Table 4
Device Use Characteristics

	Overall (n=2117)	Current Users (n=1454)	Former Users (n=663)	p-value^
Device Source, n (%)				<0.001**
Purchased it myself	1039 (49.1%)	783 (53.9%)	256 (38.6%)	
Got as a gift from friend/family	881 (41.6%)	577 (39.7%)	304 (45.9%)	
From employer	96 (4.5%)	50 (3.4%)	46 (6.9%)	
From health insurance provider	19 (0.9%)	7 (0.5%)	12 (1.8%)	
Other	82 (3.9%)	37 (2.5%)	45 (6.8%)	
Whom do you share your data with? ⌘, n (%)				
Openly on social media	211 (10.0%)	151 (10.4%)	60 (9.0%)	0.34
Privately with friends/family	1079 (51.0%)	795 (54.7%)	284 (42.8%)	<0.001**
With personal trainer	98 (4.6%)	61 (4.2%)	37 (5.6%)	0.16
With doctor(s)	175 (8.3%)	129 (8.9%)	46 (6.9%)	0.13
With no one else	865 (40.9%)	549 (37.8%)	316 (47.7%)	<0.001**

^ = chi-square analysis. ⌘ = respondents allowed to choose more than one category, therefore each row represents positive responses only. * = significant difference between groups; ** = remains significant after Benjamini-Hochberg correction for multiple comparisons.

Table 5

Reasons for Adopting Use and Influence of Device on Physical Activity

	Overall (n=2117)	Current Users (n=1454)	Former Users (n=663)	p-value^
Reason(s) for Use⌘, n (%)				
Interest in the technology	1267 (59.8%)	793 (54.5%)	474 (71.5%)	<0.001**
To monitor health variables	1308 (61.8%)	1012 (69.6%)	296 (44.6%)	<0.001**
Aid to lose weight	994 (47.0%)	754 (51.9%)	240 (36.2%)	<0.001**
Training for an event	176 (8.3%)	134 (9.2%)	42 (6.3%)	0.026**
To compete with others	322 (15.2%)	249 (17.1%)	73 (11.0%)	<0.001**
Recommended by family/friends	386 (18.2%)	267 (18.4%)	119 (17.9%)	0.82
Recommended by coach/trainer	36 (1.7%)	21 (1.4%)	15 (2.3%)	0.18
Recommended by doctor	60 (2.8%)	39 (2.7%)	21 (3.2%)	0.53
Other	185 (8.7%)	124 (8.5%)	61 (9.2%)	0.61
Influence of Device, n (%)				<0.001**
Increased PA	1464 (69.2%)	1110 (76.3%)	354 (53.4%)	
No change or reduced PA	653 (30.8%)	344 (23.7%)	309 (46.6%)	

^ = chi-square analysis. ⌘ = respondents allowed to choose more than one category, therefore each row represents positive responses only. * = significant difference between groups; ** = remains significant after Benjamini-Hochberg correction for multiple comparisons.

Primary reasons people stopped using their activity monitor, as can be seen in Table 6, were because they became bored using it (40.1%), the device broke (28.4%), or they found it uncomfortable to wear (27.9%). Only a small proportion stopped using because they had reached a goal they had set.

Table 6

Reasons for Stopping Activity Monitor Use

Reason(s) for Stopping Use⌘, n (%)	Former Users (n=663)	Men (n=185)	Women (n=478)	p-value^
The device broke	188 (28.4%)	60 (32.4%)	128 (26.8%)	0.09
I achieved my goals	49 (7.4%)	16 (8.6%)	33 (6.9%)	0.34
I didn't believe it was accurate	106 (16.0%)	31 (16.8%)	75 (15.7%)	0.53
It was uncomfortable	185 (27.9%)	47 (25.4%)	138 (28.9%)	0.69
It wasn't helping me	89 (13.4%)	18 (9.7%)	71 (14.9%)	0.16
I got a new device	32 (4.8%)	11 (5.9%)	21 (4.4%)	0.32
I became bored using it	266 (40.1%)	74 (40.0%)	192 (40.2%)	0.64

^ = chi-square analysis. ⌘ = respondents allowed to choose more than one category, therefore each row represents positive responses only. * = significant difference between groups; ** = remains significant after Benjamini-Hochberg correction for multiple comparisons.

Comparison of User Groups

Groups were compared by gender or by their device use status (current vs former) to assess whether there were particular use characteristics unique to one versus the other. The decision to group by gender was based on different outcomes found between two previous activity monitor studies, one of which had only male participants, and the other only female (Cadmus-Bertram, Marcus, Patterson, Parker, & Morey, 2015b; Jauho et al., 2015). The decision was made to compare current and former users so as to explore whether sociodemographic differences may be related to the choice to wear a device for a certain period of time.

Comparison of current and former users. Current users were older (p<0.001) and reported being in a relationship more than those who no longer use one ($\chi^2(1) = 16.9$, p<0.001). They also reported a higher income ($\chi^2(2) = 18.5$, p<0.001) and full-time employment ($\chi^2(8) = 35.1$, p<0.001) more frequently than former users. Current users had significantly higher BMI scores (p<0.001) and had lower rates of smoking (p<0.001). Former users reported fewer medical conditions (55.5%/49.6%, p=0.012), but no difference was found for perceived health. Current users reported being a current exerciser more than former users (87.5%/77.2%; $\chi^2(1) = 36.1$, p<0.001).

Current users reported an increase in PA as a result of activity monitor use more often than former users ($\chi^2(1) = 112.412$, p<0.001), and almost all of those currently wearing a device (89%) intended to continue use for at least 3 more months. Current users were reported sharing their data with friends and family more than former users ($\chi^2(1) = 25.549$, p<0.001).

Comparison of male and female users. A greater percentage of female users were white (65.1%W/59.9%M), had earned a Bachelor's degree or higher

(65.4%W/57.3%M), and had a household income less than \$50,000 (46.5%W/40.2%M). A greater proportion of male users had household incomes greater than \$100,000 (19.5%M/15.1%W) and identified as early adopters of technology (53.7%M/34.4%W). Men reported significantly higher levels of MVPA (p=0.021) and rated their health as very good or excellent more often than women (56.7%M/51.9%W, $\chi^2(1)=3.89$, p=0.049). With regard to specific medical conditions, the most widely reported were mental health disorders, asthma and hypertension, but prevalence in several conditions differed by gender. Female users reported mental health disorders (17.1%W/8%M, p<0.001) and cancer (2.4%W/0.9%M, p=0.029) at a higher rate, while men reported hypertension (12.9%M/7.5%W) and type 2 diabetes (4.1%M/2.1%W) more often. In general, men reported having no existing medical issues more often than women (55.3%M/50%W, p=0.031). Men reported lifting weights (46.2%M/34.3%W), running (52.2%/42.4%), and participating in team sports (19.7%/5.2%) more than women, while women reported a preference for walking (66.6%W/53.7%M), dancing (18.5%/4.8%), yoga (29.2%/12.1%), and aerobics (15.3%/6.4%).

There was a significant relationship between gender and the use of activity monitors among members of their social network. Women had a higher percentage of friends who used an activity monitor (64.4%W/47.5%M, $\chi^2(1)=27.3$, p<0.001), while men reported a higher proportion of having no-one in their network who owned a device (24.3%M/12.7%W, $\chi^2(1)=22.2$, p<0.001). There was no difference between men and women in the ways they shared data from their activity monitor or in their reasons for stopping use of a device.

Discussion

This study offers new insights on who activity monitor users are, why they decide to use this technology, and how they interact with their devices. When comparing across subpopulations, differences were found in how and why activity monitors were used between current and former users, as well as between women and men. Overall, the majority of respondents were highly educated and met the national recommendations for weekly PA. Most users perceived their activity monitor to be a positive influence on their health, with many having worn one for an extended length of time and planning to continue using it. Median wear time for current users was the same (7 months) as reported in a study of activity monitor users in Australia, while median wear time for former users was slightly longer (1 month) than that sample (Maher, Ryan, Ambrosi, & Edney, 2017). There was a high degree of interaction with the device, with over 90% checking it at least a few times per day, and a third of users checking it once an hour or more. Most of those who stopped using their activity monitor did so because they became bored with it, while issues with the device breaking or it being uncomfortable were other major reasons given. Fitbit was the most widely used brand with 68.9% of current and 58.4% of former users owning one. These findings are similar to a study of activity monitor users in Australia which reported that 67.5% of participants wore a Fitbit (Maher et al., 2017).

Those currently using a device reported a higher BMI and having one or more medical issues more often than former users. This is consistent with findings from the 2012 Pew Internet Research Survey where tracking of health variables was greater when one or more chronic diseases were reported (Fox & Duggan, 2013). Former users reported an interest in 'trying out new technology' as a primary reason for use and were less interested in management of weight or health variables, which could suggest that they may not have started using the device with clear intentions of changing their PA behavior. Tracking health variables, managing weight and using the device to help train for an event were reported more often by current users than former. While monitoring of health variables was reported as a primary reason for device use, a large proportion of respondents (40.9%) chose not to share their activity monitor data with anyone. Of those who did share, most choose to do so only with friends or family, with just 8.3% sharing data with their doctors. Current users reported sharing data with others more often, with almost two-thirds doing so versus only half of former users. These findings are supported by other recent studies which found similar conflicting patterns of behavior. A survey by Chen, Bauman, and Allman-Farinelli (2016) found that a majority of people reported being willing to share PA data if given the opportunity. However, in a different study when people were actually presented with the opportunity to share data with their healthcare provider, a large majority did not (Pevnick, Fuller, Duncan, & Spiegel, 2016).

More former users reported that they were given their activity monitor rather than purchasing it themselves, suggesting that voluntarily choosing to get a device could be related to the subsequent use patterns. Those who purchased the device themselves reported that it positively influenced their PA more often than those who were gifted one. This warrants further investigation, and if it were found to be the case, could have implications for the common practice of distributing these devices as part of workplace wellness initiatives. The higher reported PA by self-selecting users could be as a result of having a greater sense of autonomy, which has been shown to promote higher levels of intrinsic motivation, a predictor of positive PA behaviors (Duncan et al., 2010). Related, men reported buying a monitor for themselves and using it while training for an event more often than women, which could be an important factor when considering best-use implementation scenarios for these devices.

A major strength of this study was its large sample of activity monitor users who had decided to use these devices of their own volition, without being enrolled in an intervention. Another strength is the study sample, which was comprised of a broad scope of current and former users, some of whom had just started wearing a device, with others being long-term adoptees. This study also offers new insights from a perspective that has not been measured with traditional intervention participants. Finally, the method of data collection was a strength, as it allowed for a national distribution of the survey, resulting in responses from all 50 states.

This study is not without limitations. As this was a self-selected sample, those deciding to complete the survey may have been more motivated to speak in a positive manner about their experience of using a wearable device. Some respondents may have chosen to wear a device for reasons other than monitoring or influencing their PA and this may have influenced their responses. Also, self-report data may be subject to certain biases (such as social desirability bias) and may not accurately reflect actual use (Motl, McAuley, & DiStefano, 2005). As it was a web-based survey, it may have had an increased risk of false responses and multiple responses from a single individual. To minimize these issues, respondents were asked to detail the model of activity monitor they used and to provide a valid email address to participate, with multiple responses from the same email account removed from the analysis. It is not known which features of their device were used by survey respondents, and this likely impacted their experience. Lastly, the inclusion of questions assessing the behavioral profile of users was deemed to be overly burdensome and beyond the scope of this survey, therefore additional research is needed to explore these important relationships.

In sum, the results of this study offer new insights on how activity monitors are used outside of a clinical trial setting. Most respondents believed that their activity monitor use had a positive influence on their PA, and they provided multiple reasons for how and why they decided to use this technology. The scope of responses supports further investigation into the dynamic relationship that exists between users and their devices, including a more comprehensive assessment of how it affects their motivation and PA levels.

Chapter III

AN EXAMINATION OF THE RELATIONSHIP BETWEEN MOTIVATION, PHYSICAL ACTIVITY AND WEARABLE ACTIVITY MONITOR USE

Abstract

Background: Wearable activity monitors (AM) have been widely promoted as a means to motivate users to be more physically active, but the motivational profile of users has never been assessed.

Purpose: To profile AM users by their motivational regulation scores and investigate how profiles were associated with their moderate to vigorous physical activity (MVPA).

Methods: Current AM users (*N*=320) recruited across the United States completed a web-based survey. Motivational regulations were first assessed independently using bivariate correlations. Cluster analysis was then conducted in a series of steps, using hierarchical and non-hierarchical means, to form profiles based on respondents' motivational regulation scores. Differences in MVPA and sociodemographics between profiles were assessed using generalized linear modeling and chi-square analysis.

Results: Respondents were 19-74 years old (36.8 ± 12.8) with 75.9% women. Bivariate correlations revealed that MVPA was more highly correlated with autonomous than controlling regulations. Five motivational profiles emerged from the cluster analysis: 'High Amotivation' (n=30), 'Autonomous with High Introjected' (n=101), 'Low Overall Motivation' (n=61), 'High Controlled Motivation' (n=47), and 'Autonomous with Low

Introjected' (n=81). Profiles differed significantly across motivation and PA scores, with those characterized by more autonomous motives presenting with higher MVPA.
Conclusion: Cluster analysis is a valuable method of assessing the motivation of AM users. Differences in MVPA behavior between motivational profiles warrants longitudinal assessment of associations between AM use, motivation, and physical activity.

Background

While activity monitors have been promoted as tools to motivate users to become more active, research suggests that they may have a mixed or even a negative effect. For example, in a systematic content analysis of activity monitors, Lyons et al. (2014) found that features promoting autonomy or competence were rarely included (e.g., problem solving, exercise instruction), while those features that are more controlling (e.g., rewards, social comparison) are more common. In findings from our earlier survey, discussed in Chapter II, most activity monitor users perceived their device to be a positive influence on their health, with many having worn one for an extended length of time. 'Self-purchasers' reported that the device positively influenced their physical activity (PA) more often than those who had been gifted one, suggesting that voluntarily choosing to buy a device could be related to the subsequent motivation and use patterns. These devices have been advertised to consumers as motivational tools which can help any user become healthier (Fitbit, 2017), and they have been adopted by vast numbers of people with almost 100 million devices sold globally in 2016 (Ubrani, 2017). However, the use of wearable activity monitoring devices for increasing motivation to become more physically active has not received a sufficient amount of attention.

Self-Determination Theory (SDT) was used to guide this study as it is focused on the quality of human motivation rather than quantity, and it posits that behavior is influenced by the extent to which motivation is autonomous or controlled (Deci & Ryan, 2002). Motivation, according to SDT theory, is not a unitary concept but exists on a continuum, comprising intrinsic and extrinsic components, representing varying degrees of autonomy. Where a person is located on this continuum is determined by the extent to which their needs for competence, autonomy and relatedness have been satisfied. On one end of the SDT continuum is intrinsic motivation, which is completely self-determined and is evident in PA behavior that is done solely for the enjoyment of the task itself. On the other end of the scale is amotivation, which is neither autonomous nor controlled, but refers to the absence of any intention or motivation. Between these lay four forms of extrinsic motivation varying in degree of self-determination – integrated, identified, introjected and external regulations. Integrated regulation is characterized by an alignment of behavioral outcomes with the individual’s core values and beliefs. Identified regulation motivates behaviors that are recognized as being important to or valued by the person. Introjected regulation is related to behavior that is done to avoid guilt, shame or other negative emotions that are related to an external source. External regulation concerns behaviors that are engaged in due to pressures outside of the individual’s control, maybe to gain some type of reward or to avoid sanction (Deci & Ryan, 2008). Integrated and identified are referred to as being more self-determined or autonomous, while introjected and external are considered as non-self-determined or controlled “because the reasons for participation have not been endorsed by the individual” (Ullrich-French & Cox, 2009, p.359). With respect to PA, an individual’s motivational profile has been found to be predictive of their PA habits, with more self-determined motives associated with greater adherence to exercise programs, as well as duration and intensity of workouts (Duncan et al., 2010).

Notably, while SDT has shown itself to be applicable in this emerging field, a limitation of many studies examining SDT and PA is that a variable-centered approach evaluating the individual effects of each motivational regulation on outcomes using methods such as regression analyses has been employed in isolation. The Relative Autonomy Index, a unidimensional cumulative rating derived from motivational regulation scores, had also been commonly reported until research by Chemolli and Gagne (2014) presented compelling arguments against its usage. Measurement of regulation scores either individually or aggregated has proven inadequate in considering the multidimensionality of the SDT continuum, leaving it undetermined whether a given combination of motivational regulation scores could result in the same outcome (such as increased PA) as scoring highly in only one regulation (such as intrinsic motivation). A number of recent studies have addressed this by taking a person-centered approach, using cluster analysis to account for the different motivational relationships that may be present (Castonguay & Miquelon, 2018; Friederichs, Bolman, Oenema, & Lechner, 2015). While these studies have assessed motivational profiles and PA in adult populations, usually finding between 3 and 5 cluster solutions, none have looked at activity monitor users, a highly relevant population based on the widespread use of this type of technology. Thus, the purpose of this study was to investigate, using SDT as a guide, how activity monitor users' motivations are associated with PA behavior, both as individual variables and then in combination with each other. The aims were:

1. To measure the magnitude of each dimension of the motivation continuum (from amotivation to intrinsic motivation) among respondents and test how each type relates independently to PA behavior. *Hypothesis:* More

autonomous (self-determined) forms of motivation would be associated with higher PA levels.

2. To explore combinations of motivational regulation scores that emerged among activity monitor users. These profiles were then examined for differences in their PA behavior. *Hypothesis:* Several clusters would emerge, with profiles characterized as more self-determined reporting more positive PA behavior.

Methods

Study Design

The purpose of this study was to gather information on the motivational profile of activity monitor users in the United States. Respondents were asked to complete an online survey, comprised of 67 questions, describing their sociodemographics, PA behavior, and motivation to be physically active. This survey combined validated questionnaires alongside questions inspired by healthcare technology surveys such as the PEW Internet Research Survey (Fox & Duggan, 2013) and national population health surveys such as NHANES and NHIS. The recruitment email included a link to the Survey Monkey platform which was used for data collection. Inclusion criteria were being 18 years or older and a resident of United States.

Participants

Over 1000 respondents from our first study had stated their willingness to be contacted again for more detailed questioning on their activity monitor use. All members of this group were emailed a description of this study and a link to the survey. These participants were recruited from August to October 2017. Respondents were required to complete a new informed consent acknowledging they met inclusion criteria and understood the procedures, risks and benefits of the study. All those completing the survey were entered into a lottery to win a $100 gift card, with their chance of winning set at 1 in 500 or better. All procedures were approved by the Teachers College, Columbia University Institutional Review Board. A complete copy of the survey can be reviewed in Appendix F.

Measures

Sociodemographic profile. Participants reported their age, gender, income, race/ethnicity, employment status, education level, relationship status, and ZIP code.

Health profile. Participants were asked to report height, weight, any diagnosed medical conditions and to give a subjective rating of their own health status. Body Mass Index (BMI) was calculated using height and weight data.

Physical activity profile. The Godin Leisure Time Questionnaire, a 7-day PA recall questionnaire that reports on average how many bouts (15 minutes or greater) of mild, moderate and strenuous activity participants complete, was used to assess PA levels (Godin & Shephard, 1985). Respondents were asked their reasons for exercising, preferred mode(s) of exercise, and to rate whether they believed they do too much, too little or an appropriate amount of PA each week. Perceived PA has been found to be a predictor of future PA behavior and mortality (Zahrt & Crum, 2017).

Activity monitor use profile. Participants noted the brand and model of device they use, and how long they have been wearing it. They were asked to note how often they check their device and whom, if anyone, they share their data with. They were asked to report the extent to which wearing the device influenced their PA behavior, the amount of resistance training they do and the quality of their diet.

Motivation profile. Motivation to exercise was measured using the Behavioral Regulation in Exercise Questionnaire (BREQ 3) (Markland & Tobin, 2004; Wilson, Rodgers, Loitz, & Scime, 2006). This multidimensional 24-item questionnaire is the most widely used measure of the continuum of behavioral regulation in exercise research, and this most recent version includes a scale for integrated regulation allowing for the "full spectrum of motives" to be measured (Duncan et al., 2010, p.3).

Data Analysis

All analyses were conducted using SPSS Statistics 25.0 software (Macintosh version 25.0 SPSS Inc.). Data were screened for normality and outliers prior to analysis (Garson, 2012). Descriptive data are reported as means and standard deviations (SD) for continuous variables, while frequencies and percentages are given for categorical variables. To test for Hypothesis 1, motivational regulations were assessed independently using bivariate correlations and internal consistency reliability (Cronbach's alpha) was assessed for each subscale.

In order to test for Hypothesis 2, motivational profiles based on the regulation scores were generated by conducting a cluster analysis in a series of steps as recommended by Hair, Black, Babin, and Anderson (2010). A combination of hierarchical and non-hierarchical means was used to provide the most stable cluster solution. The aim of cluster analysis is to maximize the homogeneity of those within the clusters while also maximizing the heterogeneity between clusters. In the first step, motivational regulation scores were converted to z-scores and a hierarchical cluster analysis was carried out using Ward's method and squared Euclidian distances to identify possible cluster solutions. The ideal number of clusters was derived from the agglomeration schedule by identifying large changes in the coefficients. Cluster centers generated from this hierarchical analysis were then used as non-random starting points in the second-step, a *k*-means cluster analysis. This non-hierarchical analysis is a means of fine-tuning the findings from the hierarchical model to obtain the best cluster solution. Once clusters were formed, differences in motivational subscales, MVPA and sociodemographics between profiles were assessed using generalized linear modeling and chi-square tests. Statistical significance was set a priori at $p<0.05$ and the Bonferroni correction was used to correct for alpha-inflation due to multiple comparisons.

Results

Of 483 respondents who gave informed consent, 448 (92.8%) completed all questions. Of the completed surveys, 128 were excluded from this analysis based on the following criteria: 1) 120 respondents no longer wore an activity monitor; 2) 8 were classified as outliers based on their PA scores (>3SD from mean) or aberrant Motivational Regulation scores. Reliability analyses of the BREQ subscales in this sample are shown in Table 1. They were found to have satisfactory internal consistency values ranging from 0.77 to 0.93 (Tavakol & Dennick, 2011).

Sociodemographic and Health Profile

The sample was 75.9% women and the average age of respondents was 36.8 (± 12.8), ranging from 19 to 74 years old. Over half (52.9%) were in a cohabiting relationship and a large majority either worked full-time (64.1%) or were full-time students (14.7%). Respondents were highly educated with 69.4% having at least a bachelor's degree. The mean BMI of respondents was 27.5 (± 7.0) and over half (58.7%) identified as being in very good or excellent health. Interestingly, despite this high self-health rating, a similar proportion (58.5%) reported having at least one diagnosed medical condition. Of those with medical conditions, 37.2% had just one condition, with an additional 21.3% reporting multiple conditions. Based on reported ZIP codes, 40 states (and Washington, DC) were represented.

Activity Monitor Use Profile

The mean device weartime was over a year (14.9 months ± 12.1) and the most widely used brand was Fitbit (68.1%). A majority (65.6%) reported that their PA increased after initiating use of the device, with 39.7% reporting that they also improved their diet after wearing the device. A smaller proportion (16.9%) reported a positive change in the amount of resistance training they did after getting their activity monitor. Over half (59.1%) purchased the activity monitor themselves, with the rest receiving it as a gift. The main reason people used a device was an interest in monitoring their health variables (71.3%). Other key reasons for use were an interest in the technology itself (53.4%) and as an aid to weight loss (53.1%). Most users (90.3%) checked their device at least once a day with over a third (37.8%) interacting with the device every hour. A majority (85.6%) knew other people who also used an activity monitor but only half (51.2%) shared their data with anyone else.

Physical Activity and Motivation Profile: Hypothesis 1

The mean score on the MVPA (moderate to vigorous physical activity) section of the Godin questionnaire overall was 36.08 (± 25.59), with 71.6% scoring 24 or higher, a threshold identified by Amireault and Godin (2015) as equivalent to weekly MVPA recommendations per federal guidelines. A small proportion of respondents (13.4%) reported that they were not currently doing any exercise. Of those who did exercise, only 37.2% felt they were doing enough, with 58.2% stating that they were doing too little. A small percentage (4.7%) felt they were too active.

Mean motivational regulation and PA scores and their correlation matrix can be found in Table 1. Of the motivational regulations, identified was the most strongly endorsed with a mean score of 3.12 (on a scale of 0-4), followed by intrinsic, integrated, introjected, external and amotivation respectively. Correlations between regulations conformed in a manner characterized by Markland and Tobin (2004) as a simplex-like pattern, with subscales showing a strong positive correlation to those adjacent to them and a negative correlation to those further away. All regulation subscales were significantly correlated with MVPA, with integrated regulation showing the strongest relationship. An expected pattern, based on the underlying theoretical framework (Deci & Ryan, 2002), was found between MVPA and regulation type with more autonomous forms showing the strongest positive correlation which confirmed hypothesis 1. Amotivation and external regulation were negatively correlated with MVPA.

Table 7

Descriptive Statistics, Cronbach's Alpha and Correlation Matrix ($N = 320$)

Variable	α	*M*	SD	1	2	3	4	5	6	7
1. Amotivation	0.86	0.26	0.54	–						
2. External motivation	0.82	0.79	0.87	.330**	–					
3. Introjected motivation	0.83	2.37	1.02	-.136*	.195**	–				
4. Identified motivation	0.77	3.12	0.75	-.405**	-.179**	.410**	–			
5. Integrated motivation	0.89	2.48	1.12	-.336**	-.105	.411**	.831**	–		
6. Intrinsic motivation	0.93	2.58	1.07	-.342**	-.155**	.263**	.709**	.732**	–	
7. MVPA⌘		36.08	25.59	-.225**	-.230**	.201**	.520**	.527**	.499**	–

⌘ MVPA calculated from Godin PA Questionnaire.

Motivational Regulation Score Range: 0-4.

* $p < 0.05$

** $p < 0.001$

Cluster Analysis: Hypothesis 2

Cluster analysis was employed to address whether certain combinations of motivational regulations existed among this population (Hypothesis 2). To form profiles the agglomeration schedule from the hierarchical cluster analysis was examined and indicated changes of similar magnitude for three, four or five cluster solutions. The most sizeable change in agglomeration coefficients was from one to two clusters, but a two-cluster model offers limited value in explaining patterns and Hair et al. (2010) caution that it should only be considered when supported by strong theoretical reasoning. The three to five cluster solutions found in the hierarchical analysis were then assessed using K-Means methods to ascertain which option was most suitable. Both the three and four cluster solutions emerged having one very large, dominant cluster, which is an indication that too few clusters have been requested (Garson, 2014). Therefore, the five-cluster option was chosen as the best fit model.

Figure 1 displays the five clusters which emerged from the process: 1) a 'High Amotivation' profile (n=30, 9.4%), showing high scores on amotivation and external regulation, and low scores on the more self-determined regulations; 2) an 'Autonomous with High Introjected' profile (n=101, 31.6%) characterized by low amotivation and external regulation but high on introjected and the more self-determined regulations; 3) a 'Low Overall Motivation' profile (n=61, 19.1%), with lower scores on all subscales but in particular on the more autonomous constructs; 4) a 'High Controlled Motivation' profile (n=47, 14.7%), which was high on external and introjected motivation but low on both amotivation and the other self-determined regulations; and 5) a 'Autonomous with Low Introjected' profile (n=81, 25.3%), characterized by low scores in amotivation, external and introjected motivation, and higher scores in the more self-determined regulations.

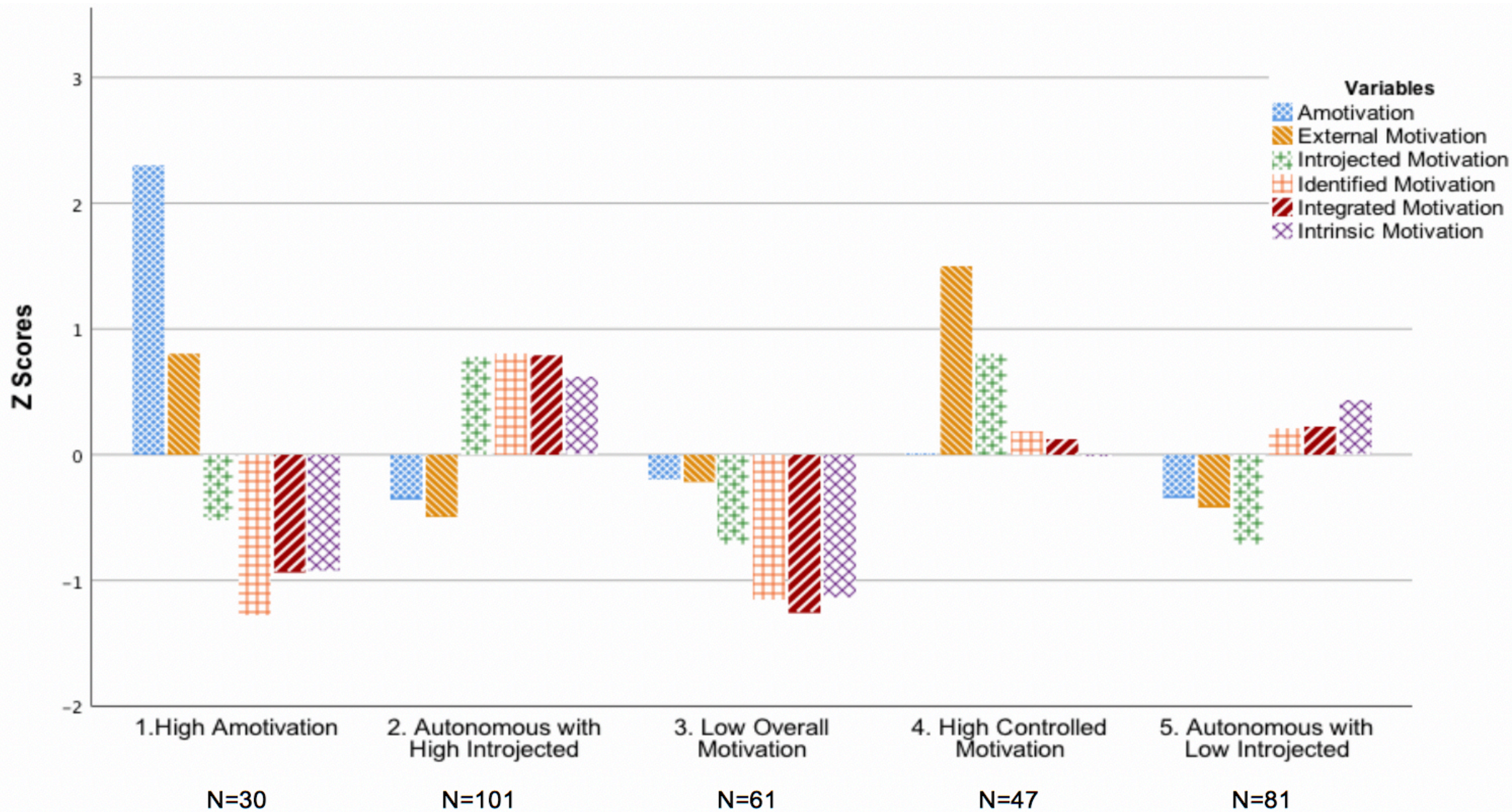

Figure 1

Motivational Profiles of Activity Monitor Users

Cluster Differences

Tables 2 and 3 illustrate the sociodemographic, MVPA and motivational characteristics of each cluster. Also included are differences between groups as assessed by chi-square analysis (Table 2) and generalized linear modeling (Table 3). Motivational regulation, MVPA and BMI scores were not normally distributed as assessed by Shapiro-Wilk's test ($p<0.05$), therefore generalized linear modeling using gamma and Tweedie distributions was employed. No differences were found in age, gender, race, education, relationship status or device source (gifted vs purchased) between cluster profiles. Significant differences were seen across clusters in MVPA and BMI ($p<0.001$), in the number of people in respondents' social networks who also had an activity monitor (multiple vs one or none) ($\chi^2(4)=10.2$, $p=0.037$), and in the number of medical conditions they reported (none, one or multiple) ($\chi^2(8)=19.9$, $p=0.011$). Significant differences were also found across clusters between each of the motivational subscales ($p<0.001$), however it should be noted that these constructs were used to identify the independent variable (cluster membership).

Cluster 2 (Autonomous with High Introjected) had the highest mean MPVA score (47.9 ± 25.5). While this was only slightly higher than Cluster 5 (Autonomous with Low Introjected) (43.3 ± 21.6), the groups displayed interesting differences. The results of post hoc tests (detailed in Appendix D), using the Bonferroni correction to adjust for multiple comparisons, showed that the groups differed significantly in both integrated and introjected regulations ($p<0.001$), with a large dissimilarity between introjected scores. Cluster 5 had the lowest score of all groups on the introjected scale, while

Cluster 2 was one of the highest. Two-thirds (66.3%) of Cluster 2's members rated their fitness as very good or excellent versus 42% of Cluster 5's membership.

Cluster 1 (High Amotivation) had the lowest MVPA score (16.9 ± 18.8) and had significantly higher amotivation and external regulation scores than any other group. The Low Motivation profile (Cluster 3) had only slightly higher MVPA (20.2 ± 19.2), but its amotivation and external regulation scores were more similar to the high active groups. Instead, this profile was characterized by having the lowest intrinsic, identified and introjected regulation scores of all groups. Both of these profiles had a higher proportion of respondents with one or more medical conditions than the highly active clusters.

The final profile which emerged was the High Controlled Motivation group (Cluster 4) which had a mean MVPA score of 31.3 (± 24.8). This profile was characterized by having the highest external and introjected motivation scores across all clusters. The average BMI of this cluster's members was slightly less than that of the two less active groups, but higher than that of the more active pair of clusters. This cluster also reported a higher prevalence of medical conditions than the more active groups.

Table 8

Sociodemographic Characteristics per Cluster

	1.High Amotivation n=30		2. Autonomous with High Introjected n=101		3. Low Motivation n=61		4. High Controlled Motivation n=47		5. Autonomous with Low Introjected n=81		*p-value*^
Variable, n (% within cluster)	n	%	n	%	n	%	n	%	n	%	
1.Gender (Female)	24	80.0	79	78.2	48	78.7	39	83.0	53	65.4	0.137
2.Race (White)	26	86.7	69	68.3	43	70.5	33	70.2	52	64.2	0.252
3.Education (BS or higher)	24	80.0	72	71.3	36	59.0	30	63.8	60	74.1	0.173
4.Relationship Status											
(partnered)	21	70.0	51	51.0	27	45.0	26	55.3	44	54.3	0.254
5. Medical Conditions	21	70.0	56	55.5	38	62.3	31	66.0	41	58.5	0.011*
6.Current Exerciser	20	66.7	97	96.0	41	67.2	40	85.1	79	97.5	< 0.001**
7.Device Source (Gift)	10	33.3	32	31.7	25	41.0	26	55.3	28	34.6	0.071
8. AM Users in Network (>1)	11	36.7	67	66.3	30	49.2	25	53.2	45	55.6	0.037*

^ = chi-square analysis

* $p < 0.05$

** $p < 0.001$

Table 9

Physical Activity, BMI and Motivational Regulations per Cluster

	1.High Amotivation n=30		2. Autonomous with High Introjected n=101		3. Low Motivation n=61		4. High Controlled Motivation n=47		5. Autonomous with Low Introjected n=81		*Model Significance*
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	*p-value*^
1.Age	36.87	12.18	38.47	13.25	35.66	13.33	32.94	10.53	37.93	13.05	0.08
2.MVPA⌘	16.90	18.83	47.90	25.54	20.15	19.20	31.30	24.76	43.20	21.60	< 0.001*
3.BMI	29.33	8.79	25.58	5.83	29.63	7.63	28.67	8.55	26.82	5.21	< 0.001*
4.Amotivation	1.61	0.73	0.06	0.19	0.16	0.23	0.28	0.39	0.07	0.18	< 0.001*
5.External regulation	1.51	0.87	0.36	0.43	0.61	0.57	2.12	0.82	0.43	0.47	< 0.001*
6.Introjected regulation	1.84	0.90	3.18	0.55	1.63	0.87	3.20	0.70	1.63	0.60	< 0.001*
7.Identified regulation	2.16	0.64	3.73	0.30	2.25	0.55	3.26	0.55	3.28	0.40	< 0.001*
8.Integrated regulation	1.44	0.72	3.37	0.60	1.08	0.51	2.63	0.99	2.74	0.77	< 0.001*
9.Intrinsic regulation	1.58	0.88	3.25	0.73	1.36	0.82	2.57	0.87	3.05	0.64	< 0.001*

^Generalized Linear Models were used due to non-normality of outcomes.

⌘ = From Godin Leisure Time Index

*$p < 0.05$

Discussion

This research provides valuable insight into the relationship between motivational patterns, sociodemographics and PA, and can be used to support future research on the use of activity monitors to support behavior change. The findings are timely given the widespread adoption of wearable technology, with many people choosing to use a device expecting that healthier behaviors will ensue. This study is, to our knowledge, the first to profile activity monitor users using motivational regulations.

The first step taken in this analysis was to measure the magnitude of each individual motivational subscale so as to allow for comparisons with earlier research. Endorsement of individual regulations by respondents was consistent with previous studies (Wilson, Rodgers, Fraser, & Murray, 2004), with identified motivation scoring the highest. Scores on the amotivation and external subscales were much lower than the more self-determined regulations, as may be expected in a population where the majority are meeting recommended levels of MVPA. While the exact score for each regulation subscale differed, the order of magnitude was identical to that found by Duncan et al. (2010) in their study on the motivation of over 1000 regular exercisers. As hypothesized, the more autonomous forms of motivation were all strongly correlated with PA ($p < 0.001$), with integrated regulation most highly associated with PA, followed by identified and then intrinsic. Introjected regulation was also positively correlated with PA, but amotivation and external regulation showed a negatively correlation ($p < 0.001$). These findings highlight both the usefulness of the regulation subscales when investigating an individual's motivation to exercise, and also the need to consider exactly how each of these motives are being altered by the component parts of a given PA intervention. If the intervention goal is to promote positive behavior change in the long-term, then allocation of a device that is more extrinsically focused in its feedback may not be the correct choice for study participants unless it is part of a larger plan (Patel, Asch, & Volpp, 2015). An assessment of the behavior change techniques present in a device should be carried out to identify its function (Mercer, Li, Giangregorio, Burns, & Grindrod, 2016) and determine its usefulness.

While the relationship between the individual motivational regulations and PA is interesting, how these regulations interact with each other could be much more important when it comes to behavior change. To address the second hypothesis, cluster analysis was used to explore the scope of this multidimensionality in activity monitor users. A range of possible cluster solutions emerged from the analysis with a five-cluster solution found to be the most stable. This is congruent with earlier studies investigating motivation and PA behaviors which found between 3 and 5 groups were most suitable when clustering regulations (Castonguay & Miquelon, 2017; Friederichs et al., 2015; Ullrich-French & Cox, 2009). One reason why a different number of clusters were found in some studies may be that several used alternate questionnaires, such as the Exercise Self-Regulation Questionnaire or earlier versions of the BREQ questionnaire, which did not measure the full spectrum of regulations. In addition, a number of these studies looked exclusively at specific groups such as those not meeting PA guidelines (Friederichs et al., 2015; Guerin & Fortier, 2012) or those with type 2 diabetes (Castonguay & Miquelon, 2018), which could explain differences in cluster solutions. A common configuration of those studies which found 3 profiles through cluster analysis was the existence of a 'self-determined' type group, a 'non-self-determined' group and some form of ‘moderate’ group. While a 3-cluster solution may have been adequate to explain differences in these studies, it could be possible that the use of activity monitors results in additional, previously unseen, motivational subgroups.

Among the profiles found in this population, certain notable differences emerged. Clusters 2 and 5 generally seemed quite alike, with similar MPVA scores and comparable higher scores in the more autonomous regulations. However, they differed significantly in their introjected regulation score (p<0.001). This is of interest because introjected regulation is regarded as more controlling, and controlled motivation has been found to be less supportive of long-term behavior change. This would suggest that even though Cluster 2 reported slightly higher MPVA, Cluster 5 (with a lower introjected score) may be more likely to adhere to their current regimen in the future. By employing instruments such as the BREQ, it may be possible to identify those at risk for unhealthier long-term behaviors, even if that is not evident from their current PA scores. A somewhat similar relationship was evident between Cluster 1 and Cluster 3, both of whom had low MVPA scores but with the former characterized by very high amotivation and the latter by its low overall motivation. While their MVPA did not differ significantly, their motivational profiles indicate that different approaches could be required to change underlying constructs that are predictive of any increase in the amount of activity they do. It was noteworthy to see a cluster of activity monitor users emerge characterized by high levels of amotivation, as one might not expect individuals amotivated for exercise to continue to wear a device. This suggests that wearing a device may not in itself indicate sufficient levels of PA are being met or even that a positive relationship with exercise exists. It is possible that use of the device may even contribute to the amotivation seen in Cluster 1, as a consistent inability to meet goals set by the monitor could lead to discouragement, stress, or a development of learned helplessness. The one remaining profile – the High Controlled Motivation Cluster – had a much lower mean MVPA score than the two highly active groups but did not differ significantly in scores within the more autonomous regulations. How it differed was that it had a significantly higher level of external regulation than either profile ($p<0.001$). External regulation has been associated with less positive health behaviors and is therefore important to consider when using activity monitors, as they often tend to offer more extrinsically-driven feedback.

A strength of this study was its investigation of a group underrepresented in the existing literature: those who have decided to use activity monitors of their own volition. The scope of data collection was also a strength, as it facilitated a national distribution of the survey, resulting in responses from across the U.S. By using cluster analysis to explore outcomes, these findings address the recommendations of earlier studies calling for exploration of scoring protocols using the entire SDT motivation spectrum (Castonguay & Miquelon, 2018; Wilson, Sabiston, Mack, & Blanchard, 2012). By using the BREQ-3 questionnaire, integrated regulation was measured, allowing for an assessment of the complete SDT continuum in relation to PA.

This study is not without limitations. As this was a cross-sectional design, it is not possible to make causal inferences. The sample was self-selecting, so those deciding to complete the survey may have different motivational or PA profiles than other activity monitor users. Some respondents may also have chosen to use a wearable device for reasons other than PA monitoring, and this could have impacted their responses. A small proportion of users (11.6%) had smartwatches such as the Apple Watch or Samsung Gear, but results did not differ significantly when the analysis was conducted with these datasets excluded. Self-report data may be subject to certain biases (such as social desirability bias) and may not accurately reflect actual behaviors (Motl et al., 2005). The ability to strictly compare findings to other research was somewhat limited due to the fact that some earlier papers did not assess the full spectrum of motives or did not investigate the subscales independently. Future studies should look at motivation and PA longitudinally, with the addition of accelerometer-derived PA measures to support self-report instruments. Cluster analysis is an exploratory method; therefore, inclusion of confirmatory analyses is recommended when assessing changes longitudinally.

While it was found that profiles characterized as being more self-determined did report more positive PA behavior, introjected and external regulation emerged as a key factors alongside more self-determined motives in determining the levels of PA reported. Although introjected motivation was a dominant factor in the cluster with the highest level of PA it is a less self-determined regulation, meaning an proliferation of this type of motivational profile in exercisers could be at odds with adoption and adherence to PA guidelines over the long-term (Hagger & Chatzisarantis, 2008). Similarly, changes in external regulation may be more significant among activity monitor users than non-users, due to the constant flow of messages from users' devices. A longitudinal observation of exercise initiates by Rodgers, Hall, Duncan, Pearson, and Milne (2010) found that after 6 months of exercising the initiates reported an increase in their self-determined forms of regulations with no change in the controlled forms. Identifying whether a similar pattern would occur among initiates using activity monitors is particularly pertinent in light of research on the behavior change techniques evident in these devices, which found that techniques promoting autonomy were rare and most were more extrinsic in nature (Lyons, Lewis, Mayrsohn, & Rowland, 2014). If extrinsic regulations are reinforced in those starting an exercise program due to concurrent activity monitor use, a greater increase in PA may occur in the short term, but to the possible detriment of long-term health behaviors. Further work is needed to assess patterns of change in motivational regulations after adopting use of an activity monitor. While an association between motivational profiles and PA was identified in the current study, additional research is needed to assess the extent to which use of an activity monitor impacts the direction and/or magnitude of this relationship.

Findings outlined in this paper build on a growing body of research exploring the relationship between PA and motivation and highlight the need to take a person-centered approach when assessing the motivation of activity monitor users. Identifying who is most likely to benefit from device-based PA monitoring, and of those, who might require additional or alternative strategies to succeed, is critical to effective behavior change intervention design (Tudor-Locke & Lutes, 2009). Use of a multidimensional approach offers the potential for a more comprehensive understanding of an individual's motivation than methods which look at regulation scores in isolation and allows researchers greater scope when considering how certain behavior change techniques influence health outcomes. Forming a behavioral profile at the beginning of an intervention could help to decide which treatment modalities are included. It could also help identify whether all participants responded to the intervention in a consistent manner by comparing results according to profiles after study completion. The broadening adoption of technology to monitor and influence health behaviors may conflict with what was previously understood to be the 'ideal' motivational profile to support a healthy lifestyle. Wearable technology has the capacity to exert a significant influence on its users and careful consideration should be taken when deciding when and how to include it as a tool when promoting behavior change.

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Appendix A

Abbreviations

AM – Activity monitor

BCT – Behavior change technique

MVPA – Moderate to vigorous physical activity

PA – Physical activity

SDT – Self-Determination Theory

Appendix B

Review of Literature

Introduction

Global rates of physical inactivity have reached pandemic proportions and associated non-communicable diseases are escalating at an alarming rate, both in the U.S. and worldwide (Blackwell, Lucas & Clarke, 2014; World Health Organization [WHO], 2014). Physical inactivity is a major risk factor for many diseases including type 2 diabetes, cardiovascular disease and some cancers (Lee et al., 2012), conditions that minorities and lower socio-economic populations are disproportionately affected by (Blackwell et al., 2014).

A robust body of research evidence exists on the beneficial effects of physical activity (PA) on illnesses such as cardiovascular disease (Sattelmair et al., 2011), cancer (Li et al., 2016), mental health (Kim et al., 2012), and type 2 diabetes (Aune, Norat, Leitzmann, Tonstad, & Vatten, 2015). A positive association has also been found to exist between PA and quality of life (Bize, Johnson, & Plotnikoff, 2007), while meeting recommended levels of aerobic PA has been associated with reduced all-mortality risk (Schoenborn & Stommel, 2011; Warburton, Nicol, & Bredin, 2006).

The 2008 Physical Activity Guidelines for Americans were created to offer direction to the public on the volume and intensity of PA needed to reduce disease risk (Garber et al., 2011; Physical Activity Guidelines Advisory Committee, 2008). However, accompanying behavior modifications among the U.S. population have not been evident, with surprisingly little change in levels of PA over recent years (Carlson, Fulton, Schoenborn, & Loustalot, 2010). Data from the 2016 National Health Interview Survey found only 50.7% of U.S. adults self-reported meeting recommended amounts of PA (Katzmarzyk, Lee, Martin, & Blair, 2017). More worrying still, in a comparison of self-reported versus accelerometer-measured PA from NHANES, only 9.5% of men and 7% of women met the recommended volume of PA according to accelerometer data, despite over 60% self-reporting they did (Tucker, Welk, & Beyler, 2011).

Rapid advances in technology have led to the adoption of numerous innovative methods of healthcare delivery and management, with use of wearable activity monitors to the fore in the area of PA, driven by broad consumer interest. Use of technology by researchers when interacting with participants is not new, with modes such as by phone, email, text-messaging (Fjeldsoe, Miller, O'Brien, & Marshall, 2012), or social media (Maher et al., 2015) frequently studied. However, most of these methods have relied on the participant to assess and self-report their behaviors, with the research team responsible for the laborious task of analyzing data and delivering feedback. Self-report can offer valuable perspective and insight to an individual’s perception of their behavior, but research has found it to be a limited measure of actual activity (Troiano et al, 2008). The widespread adoption of activity monitors by consumers, with 78 million devices sold globally in 2015 and almost 100 million sold in 2016 (Ubrani, 2017), suggests that wearable sensors should be considered as an optional component when designing interventions to address physical inactivity. These devices claim to offer accurate data measurement and persuasive feedback based on a user’s individual characteristics and behavioral profile, while also offering the promise of more cost-effective interventions and greater accessibility to those who have been historically underserved. Powell, Landman, & Bates (2014) note the appeal of using technology to influence behavior has increased with health reform and increased focus on value. However, a lack of understanding on its efficacy, or clear guidelines on its use, has limited widespread adoption across healthcare.

Despite extensive marketing exalting the supposed influence of activity monitors, the extent to which users' behaviors change is not well established. A 2007 meta-analysis (Bravata et al.) found that use of pedometers was associated with a significant increase in PA, but research is still limited on the extent to which this new generation of wearable devices, which are comparable in many ways to pedometers, but with distinct differences such as the ability to measure heart rate, determine exercise intensity or receive real-time feedback, are impacting the behaviors of users. Techniques such as self-monitoring and tailored feedback are supported by behavior change theory, with research showing that they can impact constructs such as self-efficacy, self-regulation and motivation to exercise.

The purpose of this review is to:

1. Briefly describe the origins of PA monitoring technology.
2. Outline the theoretical rationale supporting use of monitoring technology to change PA behavior.
3. Critically evaluate research findings on the use of activity monitoring technology to influence PA behavior.

While some reference is be made to the large body of pedometer research, the focus of this review is on studies using wearable devices that "measure lifestyle PA and can provide feedback beyond the display of basic activity count information" (Lewis, Lyons, Jarvis, & Baillargeon, 2015, p.2).

Background

The Burden of Disease Associated with Physical Inactivity

Obesity and comorbid diseases have escalated at a frightening rate over the past 40 years and despite ever-increasing health care expenditure the problem has continued to grow (Ogden, Carroll, Fryar, & Flegal, 2015). A measure of global disease burden – 'disability-adjusted life years' – has remained steady since 1990, but the underlying reasons have shifted from premature deaths because of communicable disease to the management of non-communicable diseases such as type 2 diabetes, hypertension and cardiovascular disease brought on by poor health behaviors (Murray et al., 2012). As the number of people with medical conditions as a result of physical inactivity have sky-rocketed, pharmaceutical manufacturers have been at the forefront of presenting potential solutions, creating increasingly powerful treatments to deal with the symptoms, and slow the progress, of various diseases. However, while treating the symptoms of illness is a vital cog in healthcare management, less headway has been made in addressing disease onset, leading to a greater prevalence of chronically ill individuals across the population (Bauer, Briss, Goodman, & Bowman, 2014). By relying on pharmaceuticals rather than health behavior change to manage disease, patients may also fail to benefit from other positive aspects of PA such as social interaction (Eime, Young, Harvey, Charity, & Payne, 2013). Another issue with disease management is non-adherence to medications (Robiner, Flaherty, Fossum, & Nevins, 2015), a problem that is liable to escalate as these diseases become more common in younger age groups and length of treatment increases. A recent meta-epidemiological study by Naci and Ioannidis (2013) found that PA interventions are similar to pharmaceutical interventions in terms of potential mortality benefits, suggesting they need to be more strongly considered as effective treatment options for non-communicable diseases.

Health Benefits of Physical Activity

While the benefits of an active lifestyle have been proclaimed since ancient times, PA has been overlooked for much of the last century as a viable alternative to medication or surgery when treating disease (Berryman, 2010). This has been, in part, due to an inability to precisely measure its effects or establish an accurate dose-response profile to treat specific complaints in a comparable manner to pharmaceuticals (Church, Earnest, Skinner, & Blair, 2007; Naci & Ioannidis, 2013). Longitudinal studies such as the College Alumni Health Study, carried over the past 50 years, have helped address this lack of knowledge and data gathered have provided us with a better understanding of approximately how much activity is needed to reduce the risk of many diseases. A significant body of research exists showing that physical inactivity and sedentary behavior are major risk factors for obesity and many comorbid diseases such as cardiovascular disease, cancer, stroke and type 2 diabetes (Lee et al., 2012; Young et al., 2016), while increased PA independently reduces disease risk and the incidence of issues such as increased blood pressure and blood glucose levels (Kokkinos & Myers, 2010). These diseases are associated with reduced quality of life and higher healthcare costs, which can lead to greater levels of poverty and inequality (Abegunde, Mathers, Adam, Ortegon, & Strong, 2007). Poor physical fitness is a modifiable risk factor, and improvements in fitness over time have been demonstrated to improve prognosis (Kodama et al., 2009; Kokkinos & Myers, 2010) with Arem et al. (2015) finding a clear dose-response between leisure-time PA and mortality.

Physical inactivity leads to increased disease risk and poor quality of life among all sections of the society ,but especially older people, those with chronic disease and those from minority/low SES populations. Keadle, McKinnon, Graubard, and Troiano (2016) found that there remains low adherence to PA guidelines among older adults (65+) and that increasing PA could have a profound effect on their health. Janssen, Carson, Lee, Katzmarzyk, and Blair (2013) compared inactive, somewhat active and active groups from within NHANES (2007-2010), NHIS (1990-2006) and US life tables (2006) data sets and found that higher levels of PA were associated with significant increases in longevity, especially in non-Hispanic populations. Using data from National Health Interview Survey, Schoenborn and Stommel (2011) found that those with chronic conditions benefited twice as much from meeting recommended levels of aerobic PA as those without existing chronic comorbidities.

Physical Activity Monitoring Technology

History of Monitoring Technology

Monitoring of PA is not a new concept. Hippocrates (460-377BC) has been described as the first epidemiologist because of his record keeping and appreciation for the virtues of exercise. The history of monitoring technology can be traced back to Leonardo da Vinci’s pedometer prototype, which he imagined could be used by the military to measure distances (Shephard & Aoyagi, 2012).

Advancements in accelerometer technology over the past 30 years has allowed for more innovative population analysis, providing more detailed data and a new level of understanding. Landmark longitudinal studies such as the Framingham Heart Study and the College Alumni Health Study provided new and fascinating insights into human behavior, influencing healthcare policy and societal norms but were somewhat limited by subjective assessment of PA, which has shown a propensity to be biased (Prince et al., 2008). One of the first large scale projects to use accelerometers to measure PA behavior was the NHANES (2003-2004), in an attempt to overcome inconsistencies in data associated with self-report (Sallis & Saelens, 2000). Uniaxial hip-worn Actigraph devices were used to provide this first instrumented assessment of PA across a large sample of the US population (Troiano et al, 2008), and large discrepancies were discovered between self-reported and accelerometer-measured PA.

The modern pedometer was developed in Japan in the 1960's by Y. Hatano and was called a 'manpo-kei' meaning '10,000-step meter'. These pedometers originally used a piezoelectric component to convert motion into an electrical signal while newer step counters have used MEMs (Micro-Electro Mechanical System) technology to determine activity. Piezoelectric devices use a threshold level to determine movement while the MEMs technology is able to gauge acceleration, thus allowing intensity of movement to be calculated (John & Freedson, 2012).

The current range of activity monitors available to consumers have evolved from these two devices, with accelerometer technology derived from research settings in a device designed to be worn by the general public on a daily basis. Most recent models use multiple sensors to track movement in three orthogonal planes (triaxial) to allow for estimation of steps taken and calories burned. Additional sensors in some devices allows users to continually monitor activity variables such as sedentary time (inclinometer), cardiovascular response (heart rate monitor), distance and location (GPS). Devices filter real time data to users, and deliver categories of feedback based on personal preferences, such as bouts of exercise or estimates of energy expenditure across light, moderate and vigorous levels of PA. It is this potential for devices to influence behavior that is of interest to many researchers currently.

Benefits Associated with Use of Monitoring Technology

PA monitoring using accelerometry, while not without its shortcomings, allows the capture of movement data using computerized means, potentially minimizing biases (Freedson, Bowles, Troiano, & Haskell, 2012). While this technology was once very expensive and only available in a research setting, there are now a multitude of cheaper consumer options, catering for all sections of the population, from athletes to children to those with chronic diseases. Limitations of accelerometer use identified during early NHANES data collection such as non-compliance, identification of non-wear times, data storage, and inaccuracy of device measures (Troiano et al, 2008), have been addressed in modern consumer devices with more fashionable waterproof designs, triaxial sensors and cloud connectivity. Activity monitors have been found to be acceptable for use not just among younger people but also in older adults (McMahon et al., 2016; Tiedemann, Hassett, & Sherrington, 2015), those with chronic disease (Mercer, Giangregorio, et al., 2016), individuals with serious mental illness (Naslund, Aschbrenner, & Bartels, 2016) and amputees (Albert, Deeny, McCarthy, Valentin, & Jayaraman, 2014).

A strength of monitoring technology that includes GPS is its ability to give context to user behavior by relating volume and intensity of activity with location (Welk & Kim, 2015). And, by being able to have users wear devices over extended periods of time, comes the potential to identify previously undetected behavioral patterns (termed ‘periodicities’) (Buman, Hu, Newman, Smeaton, & Epstein, 2016). The ability to capture light, non-exercise activity is also important as this PA, termed ‘Non-Exercise Activity Thermogenesis’, has been found to have certain health benefits, especially if a person had previously been sedentary (Levine, 2003; Levine, Vander Weg, Hill, & Klesges, 2006).

Monitoring with validated devices can also reduce certain biases such as recall or reporting bias which can lead to inconsistencies in self-report data (Motl, McAuley, & DiStefano, 2005). Vassbakk-Brovold et al. (2016) found that self-report PA data among cancer patients going through a lifestyle intervention was almost 4 times greater than when measured using an accelerometer, suggesting that fatigue associated with certain illnesses may lead to recall errors. Similarly, Tomaz, Lambert, Karpul, and Kolbe-Alexander (2014) found that fitter individuals appear to over-report PA on questionnaires more than less fit participants, perhaps due to social desirability bias. These findings support the notion that there is often a disconnect between perceived and measured PA, thus influencing the extent to which individuals may deem it necessary to exercise. An interesting study by Zahrt and Crum (2017) actually found that those perceived activity was a predictor of mortality, with those who believed themselves to be less active than others at a much greater risk.

Concerns Over Use of Monitoring Technology

While many research studies have used monitoring technology to measure PA, its use as a behavior change tool has been less common. The reasons for this are varied, with cost, accuracy and logistical concerns over data management all possible factors. Freedson et al. (2012) warn that no single measure of PA can capture the behavior of the population at large, but data gathered by accelerometry, while imperfect, is preferable over self-report. Most concern over use of technology has been whether a monitor can estimate a wearer's energy expenditure (validity), and whether it is consistent with its measurement over a set period and in different environments (reliability). If either of these are flawed, it can lead to 'user frustration, low intervention compliance and adverse reaction to the instrument, potentially impacting future public health campaigns' (Clemes, O'Connell, Rogan, & Griffiths, 2010).

Research grade accelerometers have been extensively tested with validity and reliability well established (Freedson, Melanson, & Sirard, 1998; Hendelman, Miller, Baggett, Debold, & Freedson, 2000), but validation of consumer devices has been less rigorous, and despite several studies showing reasonable accuracy across the most popular devices (Bai et al., 2016; Kooiman et al., 2015), there remain questions over the data they provide. Without knowing the specific make-up of the monitors in terms of the material used to build the device and exact type of accelerometers or optical HR sensors being used, researchers are limited in extrapolating clear data. Lack of aligned goals between manufacturers and PA interventionists mean proprietary algorithms used to determine outputs, and the effect on data of downcycling device batteries to extend weartime, are not known (Freedson et al., 2012). A pertinent issue for researchers is that the constant development of new and upgraded models means that by the time a validation study has been carried out on a device it may be already obsolete.

Relationship between Monitoring of Physical Activity and Behavior Change

Theoretical Framework for Monitoring of Physical Activity

Even when people understand that being more active will improve their quality of life and reduce healthcare costs, they tend not to increase daily PA or adhere to long-term exercise plans (Segar, Eccles, & Richardson, 2011). Behavior change is the result of an elaborate series of influencing factors, and the identification and unraveling of these various components is the basis of much behavioral research. The complexity of human behavior has led to the development of over 80 separate theories and 1700 proposed constructs (Michie et al., 2016). This situation has left many researchers overwhelmed by choice when trying to design interventions, leading to some studies being ‘theory-inspired’ rather than truly ‘theory-based’ (Michie et al., 2016).

Applying existing theory to PA interventions has proved to be difficult, with systematic reviews by Coons et al. (2012) and Teixeira, Carraca, Markland, Silva, and Ryan (2012) noting that many recent PA studies reference theory but do not actually measure any of the proposed mechanisms of action. Courneya (2010) stated that researchers need to be clearer on whether their primary outcome is a change in health or behavior measures and design their study appropriately. Williams et al. (2008) found that many PA studies that included a health behavioral component did not distinguish between determinants of adoption and adherence. This confusion has led to the development of a Theoretical Domain Framework (Cane, O'Connor, & Michie, 2012), which organizes behavioral theories and constructs into a more usable integrated framework. This can help health behavior researchers inform their intervention design by facilitating the selection of constructs which address their specific outcome goals.

Despite the difficulties in applying theory to PA research, is it clear that for an intervention to be successful, behavior change techniques (BCTs) need to be adopted in a systematic manner to influence theoretical constructs. Together they combine to form the mechanisms of action leading to behaviors being altered (Michie et al., 2016). Despite extensive research in this field, there is still not a consensus on how to link "BCTs to individual hypothesized mechanisms of action" (Michie et al., 2016, p.502). Buchan, Ollis, Thomas, and Baker (2012) noted that the most common theories used to guide PA research in recent times have been The Social Cognitive Theory (SCT) (Bandura, 2001), The Theory of Planned Behavior (Ajzen & Fishbein, 1980), The Transtheoretical Model (TTM) (Prochaska & Velicer, 1997), and The Self-Determination Theory (SDT) (Deci & Ryan, 1985). SDT, a theory which accounts for the processes that facilitate motivational development (Deci & Ryan, 2002), has emerged as a leading guide to the process by which wearable activity monitors may influence PA.

Self-Determination Theory

SDT appears to be uniquely placed to articulate how wearable activity monitors may impact the behavior of users by influencing their levels of motivation (Teixeira et al., 2012). SDT is a theory of human motivation focused on the quality of motivation rather than quantity and posits that our behavior is influenced by the extent to which our motivation is autonomous or controlled (Deci & Ryan, 2002). Motivation, according to SDT, exists on a continuum, comprising intrinsic and extrinsic components, representing varying degrees of autonomy. Where a person is located on this continuum is determined by the extent to which their needs for competence, autonomy and relatedness have been satisfied. Autonomous regulation of motivation tends to lead to it being more intrinsic, while controlled regulation tends to lead to it being more extrinsic. Motivation types in SDT have been classified on a continuum from amotivation (an absence of any motivation), to those regarded as extrinsic (external, introjected, identified and integrated), and finally intrinsic, with Teixeira et al. (2012) reporting that long-term adherence to exercise was associated with higher levels of autonomous (integrated and intrinsic) motivational regulations.

Monitoring Using Accelerometry in Physical Activity Research

Using technology to monitor PA has been associated with increased activity and improved health outcomes (Kang, Marshall, Barreira, & Lee, 2009; Vaes et al., 2013). However, despite these encouraging findings, the proposed mechanism of action for these complex behavior changes is still unclear. While baseline behavioral profiling (Napolitano et al., 2008) and short-term changes have been found to predict PA behavior, Williams et al. (2008) found that psychosocial determinants were different for adoption and maintenance of PA at 6 and 12 months. Individual feedback on levels of PA has been shown to cause greater improvements than generic information (de Vries, Kremers, Smeets, Brug, & Eijmael, 2008), while Burke et al. (2012) found that a daily feedback message delivered remotely enhanced adherence and improved weight loss. Milne, Wallman, Gordon, and Courneya (2008) found that supervised exercise soon after breast cancer treatments may help to develop a positive exercise motivational profile among survivors that could predict longer term adherence. While Heron, Tully, McKinley, and Cupples (2014) found increased step counts in both their participant groups after adopting pedometer use, those that had self-determined goals showed a significantly greater increase. In their novel study, Buman et al. (2011) suggested that peer mentors are more effective than professional staff in improving PA maintenance, especially when delivering components of SCT and SDT theories of behavior change. Silva et al. (2010) used SDT to guide their research and measured both how the effect of the intervention, and the PA itself, impacted participants. They found that levels of autonomy increased as did intrinsic exercise motivation. While many of these studies showed positive results, this type of research involves significant human interaction to oversee participant progress and offer tailored feedback, prompting consideration as to the role technology can play in automating parts of the process, thus reducing these labor costs.

Rationale for Using Technology in Behavior Change Interventions

Several studies have shown the viability of using technology to reduce labor demands associated with a behavior change program. King et al. (2014) investigated the feasibility of using technology to take the place of people and found that an automated telehealth counseling system could maintain PA increases at a similar level to that achieved by human advisors at 18 months. While that study did not use activity monitors, Pellegrini et al. (2012) used the BodyMedia Fit armband to support a weight loss intervention and found that the technology, in conjunction with monthly phone calls, produced similar results to a standard in-person program at 6 months.

The broad consumer interest in wearable monitors suggests that there is something about these devices that people find appealing, but it still unclear which aspects of use are most engaging. It may seem intuitive for people to take interest in and manage their own health, however this personal role in health metrics is a relatively new phenomenon. The majority of people have traditionally based their healthcare decisions on the advice of their physician (Abramson, Stein, Schaufele, Frates, & Rogan, 2000) or by the actions of their close peers. Most activity monitoring devices prompt users to post their health data through online social networks, a scenario which could theoretically influence the health behaviors of the user and those people connected to them according to research by Christakis and Fowler (2007). Dennison, Morrison, Conway, and Yardley (2013) found participants in their study willing to share information regarding their achievements but reluctant to disclose anything presenting themselves as weak or vulnerable. When the social element of sharing data is embraced, it may encourage greater accountability among those willing to share their information. Research by Poncela-Casasnovas et al. (2015) found that social embeddedness, as defined by the number of contacts in an online weight management community, was a predictor of weight loss, suggesting that it may be the social aspect of wearables in combination with the data from the device that encourages users.

Limitations of Technology in Behavior Change Interventions

A potential issue when using commercially produced devices it that the proprietary nature of the technology limits the ability to control the type and dose of behavior change techniques delivered. A systematic content analysis of BCTs in activity monitors discovered great disparity among different models, with most devices focusing on techniques for goal-setting, self-regulation and social support but lacking some key techniques such as planning and knowledge (Lyons, Lewis, Mayrsohn, & Rowland, 2014; Mercer, Giangregorio, et al., 2016). Even if activity monitors are found to increase motivation and PA literacy, barriers such as neighborhood safety, quality of sidewalks (Cerin et al., 2014; Sallis et al., 2016), and a perceived lack of time (Schutzer & Graves, 2004) may remain.

Maintenance of recommended levels of PA is dependent on a series of multifaceted behaviors and while the self-actualization component of SDT posits that we have an innate desire to better ourselves, it cannot be assumed that by merely giving someone their own PA data they will automatically change their behavior. In practice, many people are more likely to respond to short term than long term goals, with Segar et al. (2011, p.11) finding that “immediate payoffs motivate behavior better than distant goals”. This may also be moderated/mediated by other factors such as any associated incentives or penalties, but it should be noted that extrinsically motivated PA does not tend to lead to adherence to the same extent as when intrinsically motivated (Deci & Ryan, 2002). Ryan, Frederick, Lepes, Rubio and Sheldon (1997) noted that it is unrealistic to assume that people will always be intrinsically motivated, and that more controlling motives may also contribute to activities that are not necessarily enjoyable all the time.

A further potential complication is the variance in BCTs between different activity monitor models, with users being subjected to variable amounts of feedback data across several platforms. For example, an activity monitor wearer may receive information directly from the device, their smartphone and computer, with this feedback usually being accompanied by prompts and stimuli to encourage additional activity. This makes it even more difficult to discern the extent to which any one BCT influences a given user. Just because monitoring technology is offered as part of an intervention does not mean that participants will necessarily engage with it (Svetkey et al., 2015), and a technique that maybe suitable for one group may be detrimental to another (Williams, Michie, Dale, Stallard, & French, 2015). Monitoring of PA using technology has the potential to positively influence people in several ways but depending on the person it may also have a negative influence. From an SDT perspective, activity monitors may seem controlling to certain individuals but in others, such as the patients interviewed by Thorup et al. (2016), it allowed them a degree of autonomy from their usual cardiac rehab requirements. Therefore, it is critical that a person's baseline profile is considered. Researchers can help predict how an activity monitor (or other intervention tool) may influence behavior by identifying the BCTs present in the device using a taxonomy such as the Coventry, Aberdeen and London-Refined (CALO-RE) taxonomy (Michie et al., 2011).

Outcome of Interventions Using Monitoring to Change Behavior

History of Monitoring Technology as an Intervention Tool

Research using device-based monitoring as an instrument to influence PA behavior and impact health outcomes has progressed significantly over the past 20 years, both in terms of study design and technology used. Investigators have tailored studies and added layers of behavioral support to maximize potential health outcomes among their participants. Much of the research until recently had focused on use of pedometers and has been predominantly in a clinical population. In their systematic review, Bravata et al. (2007) found that pedometer use was associated with increased PA and decreased blood pressure and body mass index. However, they also identified significant limitations in PA monitoring research, with researchers oftentimes failing to identify the mechanism of action due to factors such as a combination of intervention tools being used (i.e. a pedometer and dietary support or counseling), or a lack of clearly articulated behavioral theory.

As activity tracking technology has evolved from basic pedometers, so too has current research design having been built on the foundations of early PA monitoring interventions. Pedometer use was initially only as a measurement tool in PA interventions rather than being an intended influence on behavior (Yamanouchi et al., 1995). Iwane et al. (2000) used pedometer-measured step counts to confirm the positive effects of PA on blood pressure among hypertensive participants, finding significant reductions in systolic blood pressure among participants who completed a walking program. However, only 83 of an initial 730 subjects completed the desired 12 weeks of walking greater than 10,000 steps per day, leading to discussion about what role the pedometer could play in encouraging adherence rather than just as a pre-post measure. Tudor-Locke et al. (2004) successfully addressed these retention issues by using pedometers as part of a behavioral intervention program (First Step Program) based on the theoretical constructs of self-efficacy and social support. This diabetes intervention was then used as a model for a number of subsequent programs in different populations and environments such as the Prince Edward Island-First Step Program (Chan, Ryan, & Tudor-Locke, 2004) which addressed a sedentary population, and the Maine in Motion Program (Croteau, Richeson, Farmer, & Jones, 2007) for older adults, which had similar components and was also based on SCT constructs (Bandura, 1977).

At the same time as these tailored interventions were being developed to assess the effects of pedometer use on individuals, researchers using the social ecological model were assessing the influence of pedometers as part of longer term (1 year +) large scale community interventions. ‘10,000 Steps Rockhampton’ in Queensland, Australia (Brown, Mummery, Eakin, & Schofield, 2006) was the first of these interventions and was used as a template for similar studies around the world (De Cocker, De Bourdeaudhuij, Brown, & Cardon, 2007).

Use of Activity Monitors to Influence Behavior Change

While there have been a limited number of studies to date addressing how use of an activity monitor influences PA behavior in adults, a strength of the completed research is that it has investigated the effects across a wide variety of population groups using different brands and models. These studies have laid the foundations for future interventions and give an interesting perspective on how activity monitors may play a role in changing lifestyles and impacting health outcomes.

Polzien, Jakicic, Tate, and Otto (2007) were early investigators of how activity monitors could influence behavior, using a device worn on the upper arm (Sensewear Pro from BodyMedia) in their weight loss trial. They found that wearing the device continually over a 12-week period increased weight loss by approximately 2 kilograms compared to a standard in-person behavioral weight loss program and by approximately 3 kilograms compared to a group wearing the device intermittently. That wearing the device only periodically detracted from any potential benefit of the technology was a surprise to investigators and they were not able to explain why this group performed worse that the control. A larger study (n=197) by Shuger et al. (2011) also used the Sensewear Pro and found that continuous monitoring using the device resulted in significant weight loss at 9 months, with even greater gains when used in conjunction with a group-based behavioral intervention. Pellegrini et al. (2012) used an updated version of the same device (BodyMedia Fit) in their intervention comparing a technology-based system against a standard in-person behavioral weight loss program, and against a combination of both. Building on the findings of Polzien et al. (2007), they found the most effective weight loss to be among the group who wore the device but also received monthly telephone support calls. Van Hoye, Boen, and Lefevre (2015) offered further support that some form of behavioral support was needed for sustained PA behavior change. Their participants (n=227) were randomly assigned into one of four groups; no feedback; feedback on steps from a pedometer; feedback on time in MVPA, energy expenditure and steps using the Sensewear Pro; or behavioral support alongside the data from the Sensewear Pro. The only significant differences were found between the group receiving behavioral support and the others. Despite these earlier findings, a recent paper by Jakicic et al. (2016) questioned the role of activity monitors as a tool in weight-loss, with a negative association being found between activity monitor use and weight-loss among their participants. Some researchers have questioned whether these findings remain relevant as the device used, which is no longer available, was worn on the upper arm and was more cumbersome than the advanced models currently available (Klasnja & Hekler, 2017).

Slootmaker, Chinapaw, Schuit, Seidell, and Van Mechelen (2009) and Reijonsaari et al. (2012) both studied the feasibility and effectiveness of using the PAM activity monitor, but neither intervention was successful in changing PA behavior. A possible reason for this was that this device, while more advanced than a pedometer, still needed to be plugged into a computer to follow for any analysis to be run or feedback given. This inconvenience, along with a poor response to the PA advice given (Slootmaker et al., 2009) was a likely influence on the participants, most of whom were already meeting PA guidelines. Although Hurling et al. (2007) also used an early activity monitor with a uniaxial accelerometer, they found significant increases in PA among their participants. Reasons for this may have been that their device (Actiwatch) was wrist-worn and could upload data via Bluetooth, reducing user burden.

Fitbit is currently the most popular activity monitor brand among consumers and has been the most widely used device in research studies (Wright, Hall Brown, Collier, & Sandberg, 2017). A study by Thorndike et al. (2014) using an early Fitbit model found that it did not affect PA but was well accepted among resident physicians in a large hospital. Modest changes in steps, blood pressure and HDL levels suggest that there is potential for use even among very busy hospital workers. Cadmus-Bertram, Marcus, Patterson, Parker, and Morey (2015) found the Fitbit One to be well-accepted in their study of overweight postmenopausal women, with the intervention group showing significant increases in MVPA, bouts of MVPA and total steps taken. Surprisingly, the control group who wore basic pedometers showed no increases in any of these measures. Ross and Wing (2016) used a similar research design to Van Hoye et al. (2015) but used the Fitbit Zip device instead of the Sensewear Pro. They found that the group using the Fitbit and also receiving regular phone calls lost more weight that the standard self-monitoring group or the device only group. Caulfield, Kaljo, and Donnelly (2014) showed encouraging results for the use of activity monitoring from their small (n=10) prospective case control study of patients recruited from a specialized COPD outpatient clinic. Their participants used a Fitbit One hip-worn device for a 6-week period and showed significant increases in step count and 6-minute walk test distance. Another small feasibility study by Ashe et al. (2015) found that PA increased and blood pressure and weight decreased among their intervention group (n=12), who wore a Fitbit activity monitor and received group-based education and social support, over a control group who only received health-related information. Wang et al. (2015) had all participants in their 6-week study wear the Fitbit One activity monitor, but half were randomized to also receive three daily text messages giving basic reminders to exercise. Actigraph-derived PA data showed a similar significant increase in MVPA in both groups pre to post, with no additional increase in the group receiving text messages after the first week. The lack of additional influence from the text messages may have been due to their generic content, as a similar study by Martin et al. (2015) used the Fitbug activity monitor with their intervention group also received text messages which were automated but had been physician-written and were theory based. The intervention group had significantly higher levels of PA than the group not receiving texts or the control group who were blinded to the activity monitor data. Using a similar design in their 12-week study of pregnant women, Choi, Lee, Vittinghoff, and Fukuoka (2016) assessed the use of a Fitbit activity monitor only versus a Fitbit plus a mobile app offering tailored daily support. Although no significant differences were found, possibly because of the low sample size (n=29), both groups increased their step count from baseline with the group with the additional support maintaining a higher level of PA throughout. Thompson, Kuhle, Koepp, McCrady-Spitzer, and Levine (2014) reported that their 48-week intervention using an activity monitor (Fitbit) and exercise counseling program was unsuccessful as participants failed to increase PA. However, mean age was 79.5 years and at the 24-week data collection the control group had shown a significant decline in PA while the intervention group had a much smaller and non-significant decrease. It is surprising that the authors did not consider maintenance of PA levels as being a positive outcome in relative terms based on the knowledge that PA levels tend to fall as we get older. Another limitation was that they did not present findings at 48 weeks, only stating that there was no change.

Jauho et al. (2015) investigated whether it was the device itself or the feedback given that influenced PA behavior. Using the Polar Active monitor in a group of 276 young men, all participants wore the device, but only half received feedback. This intervention group showed a decrease in sedentary time and increase in PA while the control (no feedback) group showed no change. Barwais and Cuddihy (2015) found positive changes in PA after use of a Gruve monitor, a device which assesses PA behavior over the previous 14 days and changes recommended goals based on activity patterns. This device incorporated a combination of predicted RMR and previous activity to determine baseline goals and used a vibrating function to encourage breaking up sedentary bouts.

Most interventions to date using technology to monitor PA have been of relatively short duration, meaning any sustained effects of device use are unknown (Raaijmakers, Pouwels, Berghuis, & Nienhuijs, 2015). Bravata et al. (2007) noted that many studies that used pedometers had issues disentangling the effect of wearing the pedometer from the contribution of other included interventional tool(s), such as PA counseling or email/text reminders. This sentiment is also referenced by other studies (Croteau, Suresh, & Farnham, 2014) as a possible limitation of more sophisticated studies has promoted with possible confounding variables.

Conclusion

This recent explosion of sensor-based monitoring technology has created a new paradigm for PA and exercise in the United States and beyond. Using technology to assist in oversight and feedback of patients/participants both during and after interventions has potential to offer a more accessible and cost-effective option, while maintaining or even increasing research quality (Marcus et al., 2007).

As activity monitoring technology continues to develop, it will conceivably incorporate more feedback data and prompts, suggesting an even greater influence on PA. However, it is premature to assume that the number of additional features can forecast the extent of any improvement in PA behavior, especially if the BCTs included are unidimensional and too similar to each other (Lyons et al., 2014; Mercer, Li, et al., 2016). Researchers must also ensure that the proposed change in PA will stimulate the appropriate physiological pathways to elicit changes in health (Powell, Paluch, & Blair, 2011).

Identifying who is most likely to benefit most from device-based monitoring of their PA, and of those, who require additional or alternative strategies to succeed, is critical to effective PA intervention design (Tudor-Locke & Lutes, 2009). Based on existing research, interventionists should continue to consider activity monitoring technology as one of their many tools, potentially aligning its use alongside other techniques to elicit desired outcomes. Even if positive behavior change outcomes are found it should not be assumed that health outcomes have also changed, as is often incorrectly concluded that the two are synonymous. The physiological pathway from behavior change to health improvement is not consistent and its complexity can be quite frustrating (Powell et al, 2011). Patel et al. (2015) warn that activity monitors should be facilitators, not drivers, of health behavior change, with patients being given devices only if there is a clear rationale and associated oversight from a healthcare professional.

As positive health benefits associated with increased PA are a consequence of sustained engagement, further research is needed to:

1. Identify why people use these devices and whether there are any shared characteristics among users.
2. Understand how activity monitors are associated with users’ motivation.

3. Determine the effect of using an activity monitor over an extended period to gauge its relationship with PA behavior and health outcomes.
4. Assess the feasibility of using PA monitoring technology in low-income, disabled and other demographic groups, identifying potential barriers to use.

This information will help to determine the extent to which monitoring technologies should be integrated alongside established lines of healthcare management to optimize the impact of PA on population health. By having a thorough baseline sociodemographic and behavioral profile of participants, and a clearly defined mechanism of change, it may eventually be possible to use these devices to elicit meaningful behavior change in a significant number of people.

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Appendix C

Study I Supplemental Data

Medical Conditions – Current versus Former Activity Monitor Users

Health and Fitness Characteristics - Medical Condition(s): Current versus Former Users

n (%)	Overall (n=2117)	Current Users (n=1454)	Former Users (n=663)	p-value^
Coronary Heart Disease	10 (0.5%)	7 (0.5%)	3 (0.5%)	0.928
Peripheral Artery Disease	6 (0.3%)	5 (0.3%)	1 (0.2%)	0.438
Hypertension	190 (9.0%)	142 (9.8%)	48 (7.2%)	0.059
Other Heart Disease	44 (2.1%)	34 (2.3%)	10 (1.5%)	0.214
Type 1 Diabetes	16 (0.8%)	11 (0.8%)	5 (0.8%)	0.995
Type 2 Diabetes	55 (2.6%)	36 (2.5%)	19 (2.9%)	0.601
Prediabetes	81 (3.8%)	62 (4.3%)	19 (2.9%)	0.12
Hyperlipidemia	35 (1.7%)	26 (1.8%)	9 (1.4%)	0.471
Cancer	42 (2.0%)	35 (2.4%)	7 (1.1%)	0.039*
COPD	16 (0.8%)	13 (0.9%)	3 (0.5%)	0.277
Asthma	308 (14.5%)	226 (15.5%)	82 (12.4%)	0.055
Liver Disease	7 (0.3%)	6 (0.4%)	1 (0.2%)	0.33
Kidney Disease	12 (0.6%)	10 (0.7%)	2 (0.3%)	0.272
HIV or AIDS	6 (0.3%)	3 (0.2%)	3 (0.5%)	0.323
Mental Health Issue	310 (14.6%)	209 (14.4%)	101 (15.2%)	0.604
Epilepsy	16 (0.8%)	13 (0.9%)	3 (0.5%)	0.277
Multiple Sclerosis	12 (0.6%)	10 (0.7%)	2 (0.3%)	0.272
Fibromyalgia	33 (1.6%)	23 (1.6%)	10 (1.5%)	0.899
Chronic Fatigue	32 (1.5%)	18 (1.2%)	14 (2.1%)	0.127
Rheumatoid Arthritis	23 (1.1%)	11 (0.8%)	12 (1.8%)	0.03*
Osteoarthitis	77 (3.6%)	54 (3.7%)	23 (3.5%)	0.78
Osteoporosis	22 (1.0%)	14 (1.0%)	8 (1.2%)	0.608
Other	317 (15.0%)	224 (15.4%)	93 (14.0%)	0.41

^ = chi-square analysis. * = significant difference between groups.

Appendix D

Study II Supplemental Data

Post hoc analysis – MVPA by Cluster

Generalized Linear Model: Pairwise Comparisons - MVPA

(I) 5 Cluster Solution	(J) 5 Cluster Solution	Mean Difference (I-J)		Std. Error	95% Wald Confidence Interval for Difference	
					Lower	Upper
1	2	-31.00	**	4.97	-40.74	-21.26
	3	-3.25		4.09	-11.27	4.78
	4	-14.40	*	5.16	-24.52	-4.28
	5	-26.30	**	5.07	-36.23	-16.36
2	1	31.00	**	4.97	21.26	40.74
	3	27.75	**	4.59	18.77	36.74
	4	16.60		5.56	5.70	27.50
	5	4.70		5.47	-6.02	15.43
3	1	3.25		4.09	-4.78	11.27
	2	-27.75	**	4.59	-36.74	-18.77
	4	-11.15	*	4.79	-20.55	-1.75
	5	-23.05	**	4.69	-32.24	-13.86
4	1	14.40	*	5.16	4.28	24.52
	2	-16.60	*	5.56	-27.50	-5.70
	3	11.15	*	4.79	1.75	20.55
	5	-11.90	*	5.65	-22.97	-0.83
5	1	26.30	**	5.07	16.36	36.23
	2	-4.70		5.47	-15.43	6.02
	3	23.05	**	4.69	13.86	32.24
	4	11.90	*	5.65	0.83	22.97

Pairwise comparisons of estimated marginal means based on the original scale of dependent variable: Q.13_Godin_MVPA

* The mean difference is significant at the .05 level.

** The mean difference remains significant at the .05 level after Bonferroni correction.

Post hoc analysis – BMI by Cluster

Generalized Linear Model: Pairwise Comparisons - BMI

(I) 5 Cluster Solution	(J) 5 Cluster Solution	Mean Difference (I-J)		Std. Error	95% Wald Confidence Interval for Difference	
					Lower	Upper
1	2	3.76	*	1.35	1.11	6.40
	3	-0.29		1.49	-3.22	2.63
	4	0.66		1.54	-2.37	3.69
	5	2.52		1.39	-0.22	5.25
2	1	-3.76	*	1.35	-6.40	-1.11
	3	-4.05	**	1.04	-6.09	-2.01
	4	-3.10	*	1.11	-5.28	-0.92
	5	-1.24		0.89	-2.99	0.51
3	1	0.29		1.49	-2.63	3.22
	2	4.05	**	1.04	2.01	6.09
	4	0.95		1.28	-1.56	3.47
	5	2.81	*	1.10	0.66	4.96
4	1	-0.66		1.54	-3.69	2.37
	2	3.10	*	1.11	0.92	5.28
	3	-0.95		1.28	-3.47	1.56
	5	1.86		1.17	-0.43	4.15
5	1	-2.52		1.39	-5.25	0.22
	2	1.24		0.89	-0.51	2.99
	3	-2.81	*	1.10	-4.96	-0.66
	4	-1.86		1.17	-4.15	0.43

Pairwise comparisons of estimated marginal means based on the original scale of dependent variable: Q.6_BMI

* The mean difference is significant at the .05 level.

** The mean difference remains significant at the .05 level after Bonferroni correction.

Post hoc analysis – Amotivation by Cluster

Generalized Linear Model: Pairwise Comparisons - Amotivation

(I) 5 Cluster Solution	(J) 5 Cluster Solution	Mean Difference (I-J)		Std. Error	95% Wald Confidence Interval for Difference Lower	Upper
1	2	1.54	**	0.37	0.82	2.26
	3	1.45	**	0.37	0.73	2.18
	4	1.33	**	0.38	0.59	2.06
	5	1.54	**	0.37	0.82	2.26
2	1	-1.54	**	0.37	-2.26	-0.82
	3	-0.09		0.05	-0.19	0.00
	4	-0.22	*	0.08	-0.38	-0.06
	5	-0.01		0.03	-0.06	0.05
3	1	-1.45	**	0.37	-2.18	-0.73
	2	0.09		0.05	0.00	0.19
	4	-0.13		0.09	-0.30	0.05
	5	0.08		0.05	-0.01	0.18
4	1	-1.33	**	0.38	-2.06	-0.59
	2	0.22	*	0.08	0.06	0.38
	3	0.13		0.09	-0.05	0.30
	5	0.21	*	0.08	0.05	0.37
5	1	-1.54	**	0.37	-2.26	-0.82
	2	0.01		0.03	-0.05	0.06
	3	-0.08		0.05	-0.18	0.01
	4	-0.21	*	0.08	-0.37	-0.05

Pairwise comparisons of estimated marginal means based on the original scale of dependent variable: BREQ_amotivation_mean

* The mean difference is significant at the .05 level.

** The mean difference remains significant at the .05 level after Bonferroni correction.

Post hoc analysis – External Regulation by Cluster

Generalized Linear Model: Pairwise Comparisons - External Regulation

(I) 5 Cluster Solution	(J) 5 Cluster Solution	Mean Difference (I-J)		Std. Error	95% Wald Confidence Interval for Difference	
					Lower	Upper
1	2	1.15	**	0.27	0.62	1.67
	3	0.90	**	0.28	0.35	1.44
	4	-0.61		0.38	-1.35	0.13
	5	1.08	**	0.27	0.55	1.61
2	1	-1.15	**	0.27	-1.67	-0.62
	3	-0.25	*	0.11	-0.46	-0.04
	4	-1.76	**	0.28	-2.30	-1.22
	5	-0.07		0.08	-0.23	0.09
3	1	-0.90	**	0.28	-1.44	-0.35
	2	0.25	*	0.11	0.04	0.46
	4	-1.51	**	0.29	-2.07	-0.95
	5	0.18		0.11	-0.04	0.40
4	1	0.61		0.38	-0.13	1.35
	2	1.76	**	0.28	1.22	2.30
	3	1.51	**	0.29	0.95	2.07
	5	1.69	**	0.28	1.14	2.24
5	1	-1.08	**	0.27	-1.61	-0.55
	2	0.07		0.08	-0.09	0.23
	3	-0.18		0.11	-0.40	0.04
	4	-1.69	**	0.28	-2.24	-1.14

Pairwise comparisons of estimated marginal means based on the original scale of dependent variable: BREQ_external_mean

* The mean difference is significant at the .05 level.

** The mean difference remains significant at the .05 level after Bonferroni correction.

Post hoc analysis – Introjected Regulation by Cluster

Generalized Linear Model: Pairwise Comparisons - Introjected Regulation

(I) 5 Cluster Solution	(J) 5 Cluster Solution	Mean Difference (I-J)		Std. Error	95% Wald Confidence Interval for Difference	
					Lower	Upper
1	2	-1.33	**	0.18	-1.69	-0.98
	3	0.21		0.17	-0.11	0.54
	4	-1.36	**	0.22	-1.79	-0.93
	5	0.21		0.16	-0.10	0.52
2	1	1.33	**	0.18	0.98	1.69
	3	1.55	**	0.14	1.27	1.83
	4	-0.03		0.20	-0.42	0.37
	5	1.54	**	0.14	1.27	1.81
3	1	-0.21		0.17	-0.54	0.11
	2	-1.55	**	0.14	-1.83	-1.27
	4	-1.58	**	0.19	-1.95	-1.20
	5	-0.01		0.12	-0.24	0.23
4	1	1.36	**	0.22	0.93	1.79
	2	0.03		0.20	-0.37	0.42
	3	1.58	**	0.19	1.20	1.95
	5	1.57	**	0.19	1.21	1.93
5	1	-0.21		0.16	-0.52	0.10
	2	-1.54	**	0.14	-1.81	-1.27
	3	0.01		0.12	-0.23	0.24
	4	-1.57	**	0.19	-1.93	-1.21

Pairwise comparisons of estimated marginal means based on the original scale of dependent variable: BREQ_introjected_mean

* The mean difference is significant at the .05 level.

** The mean difference remains significant at the .05 level after Bonferroni correction.

Post hoc analysis – Identified Regulation by Cluster

Generalized Linear Model: Pairwise Comparisons - Identified Regulation

(I) 5 Cluster Solution	(J) 5 Cluster Solution	Mean Difference (I-J)		Std. Error	95% Wald Confidence Interval for Difference	
					Lower	Upper
1	2	-1.57	**	0.09	-1.76	-1.39
	3	-0.09		0.09	-0.27	0.08
	4	-1.10	**	0.11	-1.31	-0.89
	5	-1.13	**	0.09	-1.31	-0.94
2	1	1.57	**	0.09	1.39	1.76
	3	1.48	**	0.08	1.33	1.64
	4	0.47	**	0.10	0.28	0.66
	5	0.45	**	0.08	0.28	0.61
3	1	0.09		0.09	-0.08	0.27
	2	-1.48	**	0.08	-1.64	-1.33
	4	-1.01	**	0.09	-1.19	-0.83
	5	-1.03	**	0.08	-1.19	-0.88
4	1	1.10	**	0.11	0.89	1.31
	2	-0.47	**	0.10	-0.66	-0.28
	3	1.01	**	0.09	0.83	1.19
	5	-0.02		0.10	-0.22	0.17
5	1	1.13	**	0.09	0.94	1.31
	2	-0.45	**	0.08	-0.61	-0.28
	3	1.03	**	0.08	0.88	1.19
	4	0.02		0.10	-0.17	0.22

Pairwise comparisons of estimated marginal means based on the original scale of dependent variable: BREQ_identified_mean

* The mean difference is significant at the .05 level.

** The mean difference remains significant at the .05 level after Bonferroni correction.

Post hoc analysis – Integrated Regulation by Cluster

Generalized Linear Model: Pairwise Comparisons - Integrated Regulation

(I) 5 Cluster Solution	(J) 5 Cluster Solution	Mean Difference (I-J)		Std. Error	95% Wald Confidence Interval for Difference	
					Lower	Upper
1	2	-1.93	**	0.15	-2.22	-1.64
	3	0.36	**	0.12	0.13	0.59
	4	-1.19	**	0.17	-1.51	-0.86
	5	-1.30	**	0.15	-1.58	-1.01
2	1	1.93	**	0.15	1.64	2.22
	3	2.29	**	0.12	2.05	2.53
	4	0.74	**	0.17	0.41	1.07
	5	0.63	**	0.15	0.34	0.92
3	1	-0.36	**	0.12	-0.59	-0.13
	2	-2.29	**	0.12	-2.53	-2.05
	4	-1.55	**	0.14	-1.82	-1.27
	5	-1.66	**	0.12	-1.89	-1.43
4	1	1.19	**	0.17	0.86	1.51
	2	-0.74	**	0.17	-1.07	-0.41
	3	1.55	**	0.14	1.27	1.82
	5	-0.11		0.16	-0.43	0.21
5	1	1.30	**	0.15	1.01	1.58
	2	-0.63	**	0.15	-0.92	-0.34
	3	1.66	**	0.12	1.43	1.89
	4	0.11		0.16	-0.21	0.43

Pairwise comparisons of estimated marginal means based on the original scale of dependent variable: BREQ_integrated_mean

* The mean difference is significant at the .05 level.

** The mean difference remains significant at the .05 level after Bonferroni correction.

Post hoc analysis – Intrinsic Regulation by Cluster

Generalized Linear Model: Pairwise Comparisons - Intrinsic Regulation

(I) 5 Cluster Solution	(J) 5 Cluster Solution	Mean Difference (I-J)		Std. Error	95% Wald Confidence Interval for Difference	
					Lower	Upper
1	2	-1.66	**	0.20	-2.05	-1.28
	3	0.22		0.17	-0.11	0.56
	4	-0.99	**	0.22	-1.42	-0.55
	5	-1.47	**	0.20	-1.87	-1.07
2	1	1.66	**	0.20	1.28	2.05
	3	1.89	**	0.16	1.57	2.21
	4	0.68	**	0.21	0.26	1.10
	5	0.20		0.20	-0.19	0.59
3	1	-0.22		0.17	-0.56	0.11
	2	-1.89	**	0.16	-2.21	-1.57
	4	-1.21	**	0.19	-1.58	-0.84
	5	-1.69	**	0.17	-2.02	-1.35
4	1	0.99	**	0.22	0.55	1.42
	2	-0.68	**	0.21	-1.10	-0.26
	3	1.21	**	0.19	0.84	1.58
	5	-0.48	*	0.22	-0.91	-0.05
5	1	1.47	**	0.20	1.07	1.87
	2	-0.20		0.20	-0.59	0.19
	3	1.69	**	0.17	1.35	2.02
	4	0.48	*	0.22	0.05	0.91

Pairwise comparisons of estimated marginal means based on the original scale of dependent variable: BREQ_intrinsic_mean

* The mean difference is significant at the .05 level.

** The mean difference remains significant at the .05 level after Bonferroni correction.

Appendix E

Study I Survey

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Wearable activity monitor user survey

Study Description

Thank you for taking our short 5-10 minute survey! The purpose of this study is to get a better understanding of adult users of wearable activity monitors based in the United States, what you like or dislike about your device, and how you feel it impacts your health. We plan to use this data to inform physical activity interventions in the future.

1. Confirmation of eligibility:
Do you currently wear, or have you ever worn, an electronic activity tracker?

- ◯ Yes
- ◯ No

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Wearable activity monitor user survey

Informed Consent

Teachers College, Columbia University
525 West 120th Street
New York NY 10027
212 678 3000
www.tc.edu

DESCRIPTION OF THE RESEARCH

You are invited to participate in a research study investigating the determinants of wearable activity monitor use among adults. This study consists of a survey which should take approximately 5 to10 minutes to complete. Ciarán Friel, Doctoral Candidate in Applied Physiology, Dr. Joseph T. Ciccolo, Assistant Professor and Dr. Carol Ewing Garber, Professor, will conduct this study. The survey will be conducted online with a subsection of the participants completing a short follow-up phone interview.

RISKS AND BENEFITS

There are no known risks associated with this study, although certain questions may be of a sensitive nature (e.g. history of illnesses). The study will provide no direct benefits to you. We expect that the study will help to improve the understanding of how people respond to objective monitoring of their physical activity.

PAYMENTS

You will not be compensated for your involvement in this study. All participants who complete the survey will be entered into a lottery to win a gift certificate. The odds of winning are based on the total number of participants recruited, but will be 1 in 500 or better. Approximately two months after you complete the survey, you will be notified if you are a raffle winner. If you do win, we will send you a congratulatory email that will ask you to provide an address for study staff to send the prize (a $100 Visa gift card).

DATA STORAGE TO PROTECT CONFIDENTIALITY

Your part in this study is confidential. No identifying information, including IP address, will be collected. You will only be asked to provide an email address and, if you are a raffle winner, a physical address. None of the information collected will identify you by name. Your information will be coded with a confidential participant identification number. Identifying information such as your email address will be kept in a separate file in a locked cabinet, which can be accessed only by the investigators. All electronic data will be stored on computers that are security protected. All records for this project will be handled according to Federal and State guidelines on confidentiality of health care information.

TIME INVOLVEMENT

This survey should take approximately 10 minutes to complete. If you volunteer and are selected to take part in a follow-up phone interview, it will take an additional 15-30 minutes to complete.

HOW WILL RESULTS BE USED

The results of the study will be used as part of the primary investigator's dissertation work. The findings associated with this study will be used for scientific publication. Any publications (e.g., at conferences, in journal articles, etc.) that result from this study will only use de-identified data. Your email will never be associated or connected with participation in this study.

TEACHERS COLLEGE
COLUMBIA UNIVERSITY

Wearable activity monitor user survey

Participant Rights

Teachers College, Columbia University
525 West 120th Street
New York NY 10027
212 678 3000
www.tc.edu

Principal Investigator: Ciarán Friel

Research Title: What is the demographic profile of adult activity monitor users?

Please read the text below and click to confirm you agree.

I have read the research description. I have been informed as to the purposes and procedures regarding this study.

My participation in this research is voluntary. I may refuse to participate or withdraw from participation at any time without jeopardy to future medical care, employment, student status or other entitlements.

The researcher may withdraw me from the research at his/her professional discretion.

If, during the course of the study, significant new information that has been developed becomes available which may relate to my willingness to continue to participate, the investigator will provide this information to me.

Any information derived from the research project that personally identifies me will not be voluntarily released or disclosed without my separate consent, except as specifically required by law.

If at any time I have any questions regarding the research or my participation, I can contact the investigator, who will answer my questions. The investigator's e-mail address is cpf2111@tc.columbia.edu.

If at any time I have comments or concerns regarding the conduct of the research, or questions about my rights as a research subject, I should contact the Teachers College, Columbia University Institutional Review Board /IRB. The phone number for the IRB is (212) 678-4105. Or, I can write to the IRB at Teachers College, Columbia University, 525 W. 120th Street, New York, NY, 10027, Box 151.

2. By clicking "I AGREE" below you are indicating that you are at least 18 years old, have read and understood this consent form and agree to participate in this research study:

◯ I AGREE

◯ I DECLINE

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Wearable activity monitor user survey

Demographic information

This page will ask some basic questions about who you are.

3. Do you identify as a:

4. What is your ethnicity? (Please select all that apply.)

- [ ] American Indian or Alaskan Native
- [ ] Asian or Pacific Islander
- [ ] Black or African American
- [ ] Hispanic or Latino
- [ ] White / Caucasian
- [ ] Prefer not to answer

Other (please specify)

5. Which of the following best describes your current relationship status?

- ○ Married
- ○ Widowed
- ○ Divorced
- ○ Separated
- ○ In a domestic partnership or civil union
- ○ Single, but cohabiting with a significant other
- ○ Single, never married
- ○ Prefer not to answer

6. What is your age?

7. What is the highest level of school you have completed or the highest degree you have received?

- Less than high school degree
- High school degree or equivalent (e.g., GED)
- Some college but no degree
- Associate degree
- Bachelor degree
- Graduate degree
- Prefer not to answer

8. Which of the following categories best describes your employment status?

- Employed, working full-time
- Employed, working part-time
- Not employed, looking for work
- Not employed, NOT looking for work
- Student, full-time
- Student, part-time
- Retired
- Disabled, not able to work
- Other (please specify)

9. Approximately what is your total household income?

10. In what ZIP code is your home located? (enter 5-digit ZIP code; for example, 00544 or 94305)

11. Would you classify where you live as rural, suburban or urban?

- Rural
- Suburban
- Urban

12. What type of mobile telephone do you PRIMARILY use?

- Regular cell/mobile phone (not a smartphone)
- Android
- iPhone
- Blackberry/RIM
- Windows Mobile
- I don't have a mobile phone
- Other (please specify)

13. Regarding technology, which of the following statements best describes you:

- I am always first of my peer group to get the newest technologies
- I am usually an early adopter of new technologies
- I tend to adopt new technologies when they have become established in the market
- I am generally among the last of my peers to adopt new technologies
- I am reluctant to adopting new technologies

14. Where did you find out about this survey?

- Craigslist
- LinkedIn
- Facebook
- Twitter
- Teacher's College or Columbia University website
- Email
- Other (please specify)

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Wearable activity monitor user survey

Health Profile

On this page you will be asked some basic questions about your health.

15. What is your height in feet and inches (without shoes on)?

Feet

Inches

16. What is your current weight in pounds?

17. In general, how would you rate your overall health?

- Excellent
- Very good
- Good
- Fair
- Poor

18. Have you ever been told by a healthcare professional that you have any of the following conditions (click all that apply):

- ☐ Coronary heart disease
- ☐ Peripheral artery disease
- ☐ Hypertension (high blood pressure)
- ☐ Any other heart condition
- ☐ Type 1 Diabetes
- ☐ Type 2 Diabetes
- ☐ Pre-Diabetes
- ☐ Hyperlipidemia (high levels of fats or lipids in your blood)
- ☐ Cancer
- ☐ Chronic Obstructive Pulmonary Disease (COPD)
- ☐ Asthma
- ☐ Liver disease
- ☐ Renal or kidney disease
- ☐ HIV or AIDS
- ☐ Diagnosed mental disorder such as depression, anxiety or schizophrenia
- ☐ Epilepsy
- ☐ Multiple sclerosis
- ☐ Fibromyalgia
- ☐ Chronic fatigue syndrome
- ☐ Rheumatoid arthritis
- ☐ Osteoarthritis
- ☐ Osteoporosis
- ☐ Please give details of any other condition you have that was not listed:

19. Do you currently smoke cigarettes?

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Wearable activity monitor user survey

Smoking History

20. How many cigarettes do you smoke per day (average)?

21. For how long (in months) have you smoked 5 or more cigarettes per day?

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Wearable activity monitor user survey

Exercise Profile

22. Do you currently exercise?

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Wearable activity monitor user survey

Exercise History

23. During a typical 7-day period (a week), how many times on average do you do the following kinds of exercise for more than 15 minutes during your free time? (Write the appropriate number on each line. Please write 0 if you don't do any).

STRENUOUS EXERCISE (WHEN YOUR HEART BEATS RAPIDLY)
(e.g., running, jogging, hockey, football, soccer, squash, basketball, cross country skiing, judo, roller skating, vigorous swimming, vigorous long distance bicycling)

MODERATE EXERCISE (NOT EXHAUSTING)
(e.g., fast walking, baseball, tennis, easy bicycling, volleyball, badminton, easy swimming, alpine skiing, popular and folk dancing)

MILD EXERCISE (MINIMAL EFFORT)
(e.g., yoga, archery, fishing from river bank, bowling, horseshoes, golf, snow-mobiling, easy walking)

24. During a typical 7-day period (a week), in your leisure time, how often do you engage in any regular activity long enough to work up a sweat (heart beats rapidly)?

- Often
- Sometimes
- Rarely/Never

25. What do you most often do for exercise? (Check all that apply)

- ☐ Lift weights
- ☐ Walk
- ☐ Run
- ☐ Hike
- ☐ Bike
- ☐ Swim
- ☐ Dance
- ☐ Aerobics
- ☐ Yoga
- ☐ Pilates
- ☐ Play a team sport

Other (please specify)

26. Do you feel you get too much exercise, too little exercise, or about the right amount of exercise?

- ◯ Much too much
- ◯ Somewhat too much
- ◯ Slightly too much
- ◯ About the right amount
- ◯ Slightly too little
- ◯ Somewhat too little
- ◯ Much too little

27. Why do you exercise? (Check all that apply)

- ☐ Social aspect
- ☐ For weight management
- ☐ To relieve stress
- ☐ To look good
- ☐ To train for a particular sport or event
- ☐ To reduce the risk of certain diseases
- ☐ Other (please specify)

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Wearable activity monitor user survey

History of wearable use

These questions will ask you about how you feel/felt about wearing an activity tracker. Please use the comment boxes to elaborate on your experience.

28. Do you currently use an activity monitor?

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Wearable activity monitor user survey

History of wearable use - Current user

29. Which wearable device do you use to track your activity?

30. Approximately when did you start using this device?

	Month	Year
Date		

31. Where did you get the device?

- ◯ Purchased it myself
- ◯ Got it as a gift from a friend/family member
- ◯ Got it from my employer
- ◯ Got it from my health insurance provider
- ◯ Other (please specify)

32. Why did you decide to use this activity tracker? (Check all that apply)

- ☐ Because I am interested in this type of technology
- ☐ Because I like to monitor my health-related variables
- ☐ To help me lose weight
- ☐ To help me train for a sporting event
- ☐ Because I like the gaming aspect of competing with others
- ☐ Because my friends/family recommended I get one
- ☐ Because my personal trainer or sports coach suggested I get one
- ☐ Because my doctor suggested I get one
- ☐ Other (please specify)

33. Do any of your family or friends use a wearable activity monitor? (Check all that apply)

- ☐ I'm the only person I know with one
- ☐ Mother/Father
- ☐ Brother/Sister
- ☐ Son/Daughter
- ☐ Husband/Wife/Partner
- ☐ Boyfriend/Girlfriend
- ☐ Friend(s)
- ☐ Work colleague(s)
- ☐ Other (please specify)

34. Approximately how often do you check the device?

- ◯ Multiple times per hour
- ◯ Once an hour
- ◯ A few times each day
- ◯ Less than once a day

Comments? (please specify)

35. How has wearing the device influenced your level of physical activity?

- ○ My activity levels have increased since I started wearing it
- ○ My activity levels have remained unchanged
- ○ I have reduced my level of activity since I started wearing it
- ○ I'm not sure if my activity levels have changed

Comments?

36. Who do you share your data with? (Check all that apply)

- ☐ I share it publicly on social media (Facebook, twitter, etc)
- ☐ I share it privately with friends or family
- ☐ I share it with my personal trainer or coach
- ☐ I share it with my doctor or healthcare provider
- ☐ No-one, I am the only one who sees it

Comments:

37. Do you think you'll still be wearing this activity tracker in 3 months?

- ○ Yes
- ○ No
- ○ Not Sure

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Wearable activity monitor user survey

History of wearable use - Former user

Please give as much detail as possible about your experience when you wore an activity monitor.

38. Which wearable device did you use to track your activity?
(If you aren't sure, please click OTHER and give any details you remember)

39. Approximately when did you start using this device?

	Month	Year
Date		

40. Approximately how many months did you wear the device for?

41. Where did you get the device?

- ◯ Purchased it myself
- ◯ Got it as a gift from a friend/family member
- ◯ Got it from my employer
- ◯ Got it from my health insurance provider
- ◯ Other (please specify)

42. Why did you decide to use this activity tracker? (Check all that apply)

- [ ] I was interested in trying out this type of technology
- [ ] Because I like to monitor my health-related variables
- [ ] To help me lose weight
- [ ] To help me train for a sporting event
- [ ] Because I like the gaming aspect of competing with others
- [ ] Because my friends/family recommended I get one
- [ ] Because my personal trainer or sports coach suggested I get one
- [ ] Because my doctor suggested I get one
- [ ] Other (please specify)

43. How did wearing the device influenced your level of physical activity?

- ○ My activity levels increased after I started wearing it
- ○ My activity levels remained unchanged
- ○ I reduced my level of activity after I started wearing it
- ○ I'm not sure if there was any change

Comments?

44. Who did you share your data with? (Check all that apply)

- [ ] I shared it publicly on social media (Facebook, twitter, etc)
- [ ] I shared it privately with friends or family
- [ ] I shared it with my personal trainer or coach
- [ ] I shared it with my doctor or healthcare provider
- [ ] No-one, I was the only one who saw it

Comments:

45. Why did you decide to stop using the activity tracker? (Check all that apply)

- ☐ Because the device broke
- ☐ I achieved my goals and no longer needed it
- ☐ I didn't think it was accurate
- ☐ I found the device uncomfortable or inconvenient to wear
- ☐ It wasn't helping me achieve my goals
- ☐ I started using a different device or app
- ☐ I got bored of using it

Comments?

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Wearable activity monitor user survey

Self-monitoring

A few final questions on your experience with objective monitoring technology.

46. Do you currently use any other electronic devices or apps to monitor your health?

Wearable devices

Apps

Others

47. Have you previously used any other electronic devices or apps (not mentioned prior) to monitor your health but no longer do so?

Wearable devices

Apps

Others

48. How likely is it that you would recommend an activity monitor to a friend or colleague?

Not at all likely — Extremely likely

0	1	2	3	4	5	6	7	8	9	10

49. Do you have any other comments you would like to share on your experience of using a wearable activity monitor?

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Wearable activity monitor user survey

Wrap up page

50. Please click below if you are interested in taking part in a follow-up interview on your views on wearable activity monitors.

- ◯ Yes, feel free to contact me.
- ◯ No, I'm not interested in any follow-up studies.

51. Please enter your email address below to enter into a draw for a $100 gift voucher.

Email address

Appendix F

Study II Survey

TEACHERS COLLEGE
COLUMBIA UNIVERSITY

Wearable activity monitor user survey: Subsample Follow-Up

STUDY DESCRIPTION

Thank you for taking this short 5-10 minute follow-up survey to see if you are still an activity monitor user, and to find out how you feel it has influenced the amount of activity you do. We plan to use this data to inform physical activity interventions in the future.

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Wearable activity monitor user survey: Subsample Follow-Up

INFORMED CONSENT

The next two pages outline your participant rights. Please read and click to confirm you give your informed consent.

Teachers College, Columbia University
525 West 120th Street
New York NY 10027
212 678 3000
www.tc.edu

DESCRIPTION OF THE RESEARCH
You are invited to participate in a follow-up to a survey you completed last year investigating the determinants of wearable activity monitor use among adults. This part of the study is investigating which users have continued use of an activity monitor and consists of an online survey that should take approximately 5 to10 minutes to complete. Ciarán Friel, Doctoral Candidate in Applied Physiology, Dr. Joseph T. Ciccolo, Assistant Professor and Dr. Carol Ewing Garber, Professor, will conduct this study.

RISKS AND BENEFITS
There are no known risks associated with this study, although certain questions may be of a sensitive nature (e.g. history of illnesses). The study will provide no direct benefits to you. We expect that the study will help to improve the understanding of how people respond to objective monitoring of their physical activity.

PAYMENTS
You will not be compensated for your involvement in this follow-up study. All participants who complete this follow-up survey will be entered into a lottery to win a gift certificate. The odds of winning are based on the total number of respondents but will be 1 in 500 or better. Approximately one month after you complete this survey, you will be notified if you are a winner. If you do win, we will send you a congratulatory email that will include a $100 Amazon gift card.

DATA STORAGE TO PROTECT CONFIDENTIALITY

Your part in this study is confidential. No identifying information, including IP address, will be collected. You will only be asked to provide an email address in the case you are a raffle winner and we need to send you a gift card. None of the information collected will identify you by name. Your information will be coded with a confidential participant identification number. Identifying information such as your email address will be kept in a separate file in a locked cabinet, which can be accessed only by the investigators. All electronic data will be stored on computers that are security protected. All records for this project will be handled according to Federal and State guidelines on confidentiality of health care information.

TIME INVOLVEMENT

This survey should take approximately 10 minutes to complete.

HOW WILL RESULTS BE USED

The results of the study will be used as part of the primary investigator's dissertation work. The findings associated with this study will be used for scientific publication. Any publications (e.g., at conferences, in journal articles, etc.) that result from this study will only use de-identified data. Your email will never be associated or connected with participation in this study.

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Wearable activity monitor user survey: Subsample Follow-Up

PARTICIPANT RIGHTS

Teachers College, Columbia University
525 West 120th Street
New York NY 10027
212 678 3000
www.tc.edu

Principal Investigator: Ciarán Friel

Research Title: What is the demographic profile of adult activity monitor users?

I have read the research description. I have been informed as to the purposes and procedures regarding this study.

My participation in this research is voluntary. I may refuse to participate or withdraw from participation at any time without jeopardy to future medical care, employment, student status or other entitlements.

The researcher may withdraw me from the research at his/her professional discretion.

If, during the course of the study, significant new information that has been developed becomes available which may relate to my willingness to continue to participate, the investigator will provide this information to me.

Any information derived from the research project that personally identifies me will not be voluntarily released or disclosed without my separate consent, except as specifically required by law.

If at any time I have any questions regarding the research or my participation, I can contact the investigator, who will answer my questions. The investigator's e-mail address is cpf2111@tc.columbia.edu.

If at any time I have comments or concerns regarding the conduct of the research, or questions about my rights as a research subject, I should contact the Teachers College, Columbia University Institutional Review Board /IRB. The phone number for the IRB is (212) 678-4105. Or, I can write to the IRB at Teachers College, Columbia University, 525 W. 120th Street, New York, NY, 10027, Box 151.

1. By clicking "I AGREE" below you are indicating that you are at least 18 years old, have read and understood this consent form and agree to participate in this research study:

- ◯ I AGREE
- ◯ I DECLINE

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Wearable activity monitor user survey: Subsample Follow-Up

DEMOGRAPHIC INFORMATION

This page will ask some basic questions about who you are.

2. What is your age?

3. Which of the following categories best describes your employment status?

- Employed, working full-time
- Employed, working part-time
- Not employed, looking for work
- Not employed, NOT looking for work
- Student, full-time
- Student, part-time
- Retired
- Disabled, not able to work
- Other (please specify)

4. Approximately what is your total household income?

5. What type of mobile telephone do you PRIMARILY use?

- ◯ Android
- ◯ iPhone
- ◯ Blackberry/RIM
- ◯ Windows Mobile
- ◯ Regular cell/mobile phone (not a smartphone)
- ◯ I don't have a mobile phone
- ◯ Other (please specify)

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Wearable activity monitor user survey: Subsample Follow-Up

HEALTH PROFILE

On this page you will be asked some basic questions about your health.

6. What is your height in feet and inches (without shoes on)?

Feet

Inches

7. What is your current weight in pounds?

8. In general, how would you rate your overall health?

- Excellent
- Very good
- Good
- Fair
- Poor

9. In general, how would you rate your fitness level?

- Excellent
- Very good
- Good
- Fair
- Poor

10. Since completing the initial survey, have you been told by a healthcare professional that you have any new conditions (click all that apply):

- [ ] Coronary heart disease
- [ ] Peripheral artery disease
- [ ] Hypertension (high blood pressure)
- [ ] Any other heart condition
- [ ] Type 1 Diabetes
- [ ] Type 2 Diabetes
- [ ] Pre-Diabetes
- [ ] Hyperlipidemia (high levels of fats or lipids in your blood)
- [ ] Cancer
- [ ] Chronic Obstructive Pulmonary Disease (COPD)
- [ ] Asthma
- [ ] Liver disease
- [ ] Renal or kidney disease
- [ ] HIV or AIDS
- [ ] Diagnosed mental disorder such as depression, anxiety or schizophrenia
- [ ] Epilepsy
- [ ] Multiple sclerosis
- [ ] Fibromyalgia
- [ ] Chronic fatigue syndrome
- [ ] Rheumatoid arthritis
- [ ] Osteoarthritis
- [ ] Osteoporosis
- [ ] Please give details of any other condition you have that was not listed:

11. Do you currently smoke cigarettes?

12. Do you currently exercise?

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Wearable activity monitor user survey: Subsample Follow-Up

EXERCISE PROFILE

13. During a typical 7-day period, how many times on average do you do the following kinds of exercise for more than 15 minutes?
(Please enter 0 if you don't do any)

STRENUOUS EXERCISE (WHEN YOUR HEART BEATS RAPIDLY)
(e.g., running, jogging, hockey, football, soccer, squash, basketball, cross country skiing, judo, vigorous swimming, long distance bicycling)
Number of times per week:

MODERATE EXERCISE (NOT EXHAUSTING)
(e.g., fast walking, baseball, tennis, easy bicycling, volleyball, badminton, easy swimming, alpine skiing, popular & folk dancing)
Number of times per week:

MILD EXERCISE (MINIMAL EFFORT)
(e.g., yoga, archery, fishing from river bank, bowling, horseshoes, golf, easy walking)
Number of times per week:

14. During a typical 7-day period, in your leisure time how often do you engage in any regular activity long enough to work up a sweat (heart beats rapidly)?

- Often
- Sometimes
- Rarely/Never

15. What do you most often do for exercise? (Check all that apply)

- ☐ Lift weights
- ☐ Walk
- ☐ Run
- ☐ Hike
- ☐ Bike
- ☐ Swim
- ☐ Dance
- ☐ Aerobics
- ☐ Yoga
- ☐ Pilates
- ☐ Play a team sport

Other (please specify)

16. Do you feel you get too much exercise, too little exercise, or about the right amount of exercise?

- ○ Much too much
- ○ Somewhat too much
- ○ Slightly too much
- ○ About the right amount
- ○ Slightly too little
- ○ Somewhat too little
- ○ Much too little

17. Why do you exercise? (Check all that apply)

- ☐ Social aspect
- ☐ For weight management
- ☐ To relieve stress
- ☐ To look good
- ☐ To train for a particular sport or event
- ☐ To reduce the risk of certain diseases
- ☐ Other (please specify)

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Wearable activity monitor user survey: Subsample Follow-Up

HISTORY OF WEARABLE USE

These questions will ask you about how you feel/felt about wearing an activity tracker. Please use the comment boxes to elaborate on your experience.

18. Do you still use an activity monitor?

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Wearable activity monitor user survey: Subsample Follow-Up

HISTORY OF WEARABLE USE - CURRENT USER

19. Which wearable device do you currently use to track your activity?

20. Approximately how many months have you been wearing this device for?

21. Where did you get the device?

- Purchased it myself
- Got it as a gift from a friend/family member
- Got it from my employer
- Got it from my health insurance provider
- Other (please specify)

22. Why did you decide to use this activity tracker? (Check all that apply)

- ☐ Because I am interested in this type of technology
- ☐ Because I like to monitor my health-related variables
- ☐ To help me lose weight
- ☐ To help me train for a sporting event
- ☐ Because I like the gaming aspect of competing with others
- ☐ Because my friends/family recommended I get one
- ☐ Because my personal trainer or sports coach suggested I get one
- ☐ Because my doctor suggested I get one
- ☐ Other (please specify)

23. Do any of your family or friends use a wearable activity monitor? (Check all that apply)

- ☐ I'm the only person I know with one
- ☐ Mother/Father
- ☐ Brother/Sister
- ☐ Son/Daughter
- ☐ Husband/Wife/Partner
- ☐ Boyfriend/Girlfriend
- ☐ Friend(s)
- ☐ Work colleague(s)
- ☐ Other (please specify)

24. Approximately how often do you check the device?

- ○ Multiple times per hour
- ○ Once an hour
- ○ A few times each day
- ○ Less than once a day

Comments? (please specify)

25. Who do you share your data with? (Check all that apply)

- ☐ I share it publicly on social media (Facebook, twitter, etc)
- ☐ I share it privately with friends or family
- ☐ I share it with my personal trainer or coach
- ☐ I share it with my doctor or healthcare provider
- ☐ No-one, I am the only one who sees it

Comments:

26. How has wearing the device influenced your level of physical activity?

- ○ My activity levels have increased since I started wearing it
- ○ My activity levels have remained unchanged
- ○ I have reduced my level of activity since I started wearing it
- ○ I'm not sure if my activity levels have changed

Comments?

27. Has wearing the device influenced the amount of weight training you do?

- ○ I have trained more with weights since I started wearing it
- ○ The amount of training I do with weights has remained unchanged
- ○ I have reduced the amount of weight training I do since I started wearing it
- ○ I'm not sure if the amount of weight training I do has changed

Comments?

28. How has wearing the device influenced the quality of your diet?

- ○ My diet has gotten better since I started wearing it
- ○ My diet has remained unchanged
- ○ My diet has become worse since I started wearing it
- ○ I'm not sure if my dietary habits have changed

Comments?

29. Do you think you'll still be wearing this activity tracker in 3 months?

- ◯ Yes
- ◯ No
- ◯ Not Sure

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Wearable activity monitor user survey: Subsample Follow-Up

HISTORY OF WEARABLE USE - FORMER USER

Please give as much detail as possible about your experience when you wore an activity monitor.

30. Which wearable device did you use to track your activity?
(If you aren't sure, please click OTHER and give any details you remember)

31. Approximately how many months did you wear the device for?

32. Where did you get the device?

- Purchased it myself
- Got it as a gift from a friend/family member
- Got it from my employer
- Got it from my health insurance provider
- Other (please specify)

33. Why did you decide to use this activity tracker? (Check all that apply)

- [ ] I was interested in trying out this type of technology
- [ ] Because I like to monitor my health-related variables
- [ ] To help me lose weight
- [ ] To help me train for a sporting event
- [ ] Because I like the gaming aspect of competing with others
- [ ] Because my friends/family recommended I get one
- [ ] Because my personal trainer or sports coach suggested I get one
- [ ] Because my doctor suggested I get one
- [ ] Other (please specify)

34. How did wearing the device influenced your level of physical activity?

- ○ My activity levels increased after I started wearing it
- ○ My activity levels remained unchanged
- ○ I reduced my level of activity after I started wearing it
- ○ I'm not sure if there was any change

Comments?

35. Did wearing the device influenced the amount of weight training you did?

- ○ I trained more with weights when I was wearing it
- ○ The amount of training I did with weights remained unchanged
- ○ I reduced the amount of training I did with weights after I started wearing it
- ○ I'm not sure if the amount of weight training I did changed

Comments?

36. How did wearing the device influence the quality of your diet?

- ◯ My diet was better after I started wearing it
- ◯ My diet remained unchanged after I started wearing it
- ◯ My diet became worse after I started wearing it
- ◯ I'm not sure if my dietary habits changed while I wore it

Comments?

37. Who did you share your data with? (Check all that apply)

- ☐ I shared it publicly on social media (Facebook, twitter, etc)
- ☐ I shared it privately with friends or family
- ☐ I shared it with my personal trainer or coach
- ☐ I shared it with my doctor or healthcare provider
- ☐ No-one, I was the only one who saw it

Comments:

38. Why did you decide to stop using the activity tracker? (Check all that apply)

- ☐ Because the device broke
- ☐ I achieved my goals and no longer needed it
- ☐ I didn't think it was accurate
- ☐ I found the device uncomfortable or inconvenient to wear
- ☐ It wasn't helping me achieve my goals
- ☐ I started using a different device or app
- ☐ I got bored of using it

Comments?

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Wearable activity monitor user survey: Subsample Follow-Up

WHY YOU EXERCISE....(SURVEY IS ALMOST DONE!)

Why do you engage in exercise?
Please indicate to what extent each of the following items is true for you. Please note that there are no right or wrong answers and no trick questions. We simply want to know how you personally feel about exercise.

39. It's important to me to exercise regularly

◯ 0 (not true for me) ◯ 1 ◯ 2 (somewhat true) ◯ 3 ◯ 4 (very true for me)

40. I don't see why I should have to exercise

◯ 0 (not true for me) ◯ 1 ◯ 2 (somewhat true) ◯ 3 ◯ 4 (very true for me)

41. I exercise because it's fun

◯ 0 (not true for me) ◯ 1 ◯ 2 (somewhat true) ◯ 3 ◯ 4 (very true for me)

42. I feel guilty when I don't exercise

◯ 0 (not true for me) ◯ 1 ◯ 2 (somewhat true) ◯ 3 ◯ 4 (very true for me)

43. I exercise because it is consistent with my life goals

◯ 0 (not true for me) ◯ 1 ◯ 2 (somewhat true) ◯ 3 ◯ 4 (very true for me)

44. I exercise because other people say I should

◯ 0 (not true for me) ◯ 1 ◯ 2 (somewhat true) ◯ 3 ◯ 4 (very true for me)

45. I value the benefits of exercise

◯ 0 (not true for me) ◯ 1 ◯ 2 (somewhat true) ◯ 3 ◯ 4 (very true for me)

46. I can't see why I should bother exercising

◯ 0 (not true for me) ◯ 1 ◯ 2 (somewhat true) ◯ 3 ◯ 4 (very true for me)

47. I enjoy my exercise sessions

◯ 0 (not true for me) ◯ 1 ◯ 2 (somewhat true) ◯ 3 ◯ 4 (very true for me)

48. I feel ashamed when I miss an exercise session

◯ 0 (not true for me) ◯ 1 ◯ 2 (somewhat true) ◯ 3 ◯ 4 (very true for me)

49. I consider exercise part of my identity

◯ 0 (not true for me) ◯ 1 ◯ 2 (somewhat true) ◯ 3 ◯ 4 (very true for me)

50. I take part in exercise because my friends/family/partner say I should

◯ 0 (not true for me) ◯ 1 ◯ 2 (somewhat true) ◯ 3 ◯ 4 (very true for me)

51. I think it is important to make the effort to exercise regularly

◯ 0 (not true for me) ◯ 1 ◯ 2 (somewhat true) ◯ 3 ◯ 4 (very true for me)

52. I don’t see the point in exercising

◯ 0 (not true for me) ◯ 1 ◯ 2 (somewhat true) ◯ 3 ◯ 4 (very true for me)

53. I find exercise a pleasurable activity

◯ 0 (not true for me) ◯ 1 ◯ 2 (somewhat true) ◯ 3 ◯ 4 (very true for me)

54. I feel like a failure when I haven’t exercised in a while

◯ 0 (not true for me) ◯ 1 ◯ 2 (somewhat true) ◯ 3 ◯ 4 (very true for me)

55. I consider exercise a fundamental part of who I am

◯ 0 (not true for me) ◯ 1 ◯ 2 (somewhat true) ◯ 3 ◯ 4 (very true for me)

56. I exercise because others will not be pleased with me if I don't

◯ 0 (not true for me) ◯ 1 ◯ 2 (somewhat true) ◯ 3 ◯ 4 (very true for me)

57. I get restless if I don't exercise regularly

◯ 0 (not true for me) ◯ 1 ◯ 2 (somewhat true) ◯ 3 ◯ 4 (very true for me)

58. I think exercising is a waste of time

◯ 0 (not true for me) ◯ 1 ◯ 2 (somewhat true) ◯ 3 ◯ 4 (very true for me)

59. I get pleasure and satisfaction from participating in exercise

◯ 0 (not true for me) ◯ 1 ◯ 2 (somewhat true) ◯ 3 ◯ 4 (very true for me)

60. I would feel bad about myself if I was not making the time to exercise

◯ 0 (not true for me) ◯ 1 ◯ 2 (somewhat true) ◯ 3 ◯ 4 (very true for me)

61. I consider exercise consistent with my values

◯ 0 (not true for me) ◯ 1 ◯ 2 (somewhat true) ◯ 3 ◯ 4 (very true for me)

62. I feel under pressure from my friends/family

◯ 0 (not true for me) ◯ 1 ◯ 2 (somewhat true) ◯ 3 ◯ 4 (very true for me)

63. I feel under pressure from my friends/family

◯ 0 (not true for me) ◯ 1 ◯ 2 (somewhat true) ◯ 3 ◯ 4 (very true for me)

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Wearable activity monitor user survey: Subsample Follow-Up

OBJECTIVE MONITORING TECHNOLOGY

A few final questions on your experience with objective monitoring technology.

64. What aspect of the device (if any) did you find most impactful on your physical activity?

65. Do you currently use any other electronic devices or apps to monitor your health?

Wearable devices

Apps

Others

66. How likely is it that you would recommend an activity monitor to a friend or colleague?

Not at all likely — Extremely likely

0	1	2	3	4	5	6	7	8	9	10

67. Do you have any other comments you would like to share regarding your activity monitor experience?

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THANK YOU

Thanks so much for being part of this valuable study!